Erasmus University Rotterdam

MSc Thesis

Health Economics

Curbing the trend: Estimating Hospital-specific expenditure growth through regional variation

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Abstract

We study variation in individual annual hospital expenditure trends for all hospitals in the Netherlands for the period 2011-2017. The trends reflect the average annual expenditure patterns of all persons living in the Hospital Referral Region for each hospital. This allows us to study which hospitals may achieve expenditure savings compared to a national average expenditure trend. We find large variation in hospital-specific expenditure trends. The five hospitals with the largest savings show an average regional trend of €24.70, after controlling for regional demographics and socioeconomic status. This is equivalent to a 2.2% annual reduction relative to 2011 per-person expenditure levels. However, we find that hospitals who are able to achieve cost savings relative to the national trend were typically more expensive at the starting period of our analysis. Adjusting for this regression to the mean effect we find that the saving trend of 24.70 euros per person per year diminish to 6.05 euros. Relative to 2011 expenditure levels, this still represents a total expenditure savings of 3.2% over the 6-year period 2011-2017. We find no relation of hospital-expenditure trends to expenditure trends in primary care or other non-hospital care.

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1 Introduction

In their 2018 forecast of health care expenditures (HCE), the Dutch National Institute for Public Health forecasts that total HCE will grow at an annual rate of 2.9%, leading them to double by 2040 relative to their 2015 value. An estimated two-thirds of this total growth is attributed to supply-side factors.(Verschuuren et al., 2018). As newer medicines and procedures are introduced, the overall quality of care is increased. This makes it all the more valuable to identify whether particular health care providers are able to find ways to buck the national trend by curtailing their expenditure growth.

In the Netherlands, specialist care accounts for 27.9% of total health care expenditure, equivalent to 3.7% of GDP (CBS, 2018). Specialist care is delivered through 105 general and 8 academic hospitals as of 2018 (RIVM, 2018). Hospitals may vary by their spending patterns. For example they may incur different costs per procedure, or they may differ in the amount of procedures they prescribe for a particular diagnosis. The task of curtailing total specialist care expenditures therefore relies on hospitals improving their efficiency, as well as limiting volume. In this paper, we explore the growth in hospital care expenditures for the period 2011 to 2017. Particularly, we aim to study whether the growth in expenditures is uniform across the Netherlands, or whether the trend in spending differs among areas surrounding each hospital. This allows us to study whether the trend towards more expensive health care is unavoidable given a rising demand, or whether some hospital-specific areas are able to limit or revert the tendency towards higher expenditures. Our goal is to rank a set of comparable hospitals by their regional spending trends. This may reveal the inter-hospital differences in expenditure increases, and potentially help outline front-running hospitals when it comes to curtailing expenditure growth. We note that the analysis relies on the assumption that a majority of people use the hospital closest to them, and that no measure is given for health outcomes in the region, such that trends towards lower expenditures do not necessitate gains in efficiency.

To our knowledge, no such analysis of hospital-specific expenditures has been performed for the Netherlands. Rather than hospital-specific expenditure trend analysis, analyses of efficiency are more common. These compare expenditure levels relative to an outcome indicator. In the literature, the primary method of comparing hospital efficiencies is Data Envelopment Analysis (DEA). In the hospital sector, this is done by estimating hospital performance relative to the frontier of most efficiently delivered care. Alternatively, Stochastic Frontier Analysis (SFA) is used to control for random shocks in expenses or output. Results suggest that efficiency in providing care varies greatly among hospitals, for almost every country studied (Kohl et al., 2018). Evidence on Dutch hospitals suggests that significant differences in hospital efficiencies do exist. The DEA-estimated differences in efficiencies are found to have grown over the years (van Ineveld et al., 2016) and to be unrelated to hospital board compensation (Blank and van Hulst, 2011). It has also been shown that hospitals with high physician intensity are particularly inefficient (Blank and Valdmanis, 2010). We aim to extend these results by investigating whether these differences are reflected in the regional variations in HCE. We are particularly interested to find hospitals which are able to produce a regional trend in hospital expenditures below the national mean, therefore reverting a national trend towards more expensive hospital expenditures.

We also consider a potential source of hospital-specific trends towards lower expenditures. A particular trend in the Netherlands to make health care more efficient is that of primary care substitution. Where deemed possible, procedures currently performed by hospital specialists are being delegated to the primary care physician. When primary care physicians can deliver the same care more affordably, gains in efficiency are realised. Following recommendations from the specially appointed 'Taskforce Healthcare Expenditures' to keep care to its essentials and displace treatment to primary care physicians, multiple initiatives have been taken by insurers, hospitals, and primary care organizations to implement substitutions (van Hoof et al., 2016). Primary care physicians would have a cost-saving potential by taking over some specialist care for the chronically ill, as well as for mild psychological afflictions and basic dermatology (van Dijk et al., 2013). We are therefore particularly interested in analysing the relationship between aggregate specialist healthcare expenditures and primary care expenditures. If primary care physicians are able to perform procedures more efficiently, we should expect an inverse relation between the two variables in regions exercising substitution, with their sum being lower as a result.

We aim to supplement existing literature on variations in Dutch hospital expenditures. We use a framework of Hospital Referral Regions (HRRs) to link regional trends in hospital expenditures to particular hospitals. Specifically, we want to see for each hospital whether the surrounding HRR has distinctly lower or higher hospital expenditure growth than national trends, which might inform us on the source of recent increases in per-capita hospital expenditures. The advantage of this approach is that it makes use of publicly available aggregated expenditure data. We will also study whether, controlling for the demographic composition of the area surrounding the hospital, hospitals with a significant regional trend started the period of analysis with significantly higher overall expenditures. Should a hospital present a significantly negative regional trend, this may reflect a successful policy change towards efficiency if it was not particularly expensive to begin with. However, if the hospital area started the period of analysis with excessive expenditure levels, the hospital-specific decrease in expenditures may just reflect a correction of previous inefficiencies.

Section 2 will make explicit our research objective, after which the theoretical framework is established in section 3. Section 4 reports the data sources used, with section 5 describing the econometric methods. Section 6 reports results, after which section 7 concludes.

2 Research Objective

We will study regional trends in the areas surrounding hospitals, to ascertain whether national trends in health care expenditure are shared by each hospital, or whether particular hospitals are able to limit their expense growth. We also compare hospital-specific trends with the ex-ante spending level in the starting period of analysis, 2011. A hospital-specific trend may indicate that the hospital is achieving expenditure savings, but this should be easier for hospitals who had high excess expenditures to start with. Comparing hospital trends and ex-ante levels should provide an indication whether hospitals achieving cost savings are compensating for a previous excessive spending level, or whether they are achieving cost savings in excess of the national mean.

We are also interested in the correlation of hospital-specific trends with trends in primary care expenses, to see whether a region-specific trend in specialist care expense may be founded in substitution to primary care physicians. If this is the case, we should expect the respective trends to be inversely correlated.

In summary, we formulate the following research questions:

1. *What are the variations in hospital expenditure trends?*
2. *Are hospital expenditure trends related to the expenditure level in 2011?*
3. *Are hospital expenditure trends inversely related to primary care expenditure trends?*

3 Theoretical Framework

We model hospital-specific expenditure trends by means of the regional expenditure data from areas directly surrounding the hospital. This method implicitly assumes that a region close to a hospital gets most, if not all of its specialist care from that particular hospital. Gains in hospital efficiency or per-patient care volume should then be reflected in the aggregate hospital expenditures for regions surrounding the hospital. We denote the region making use of the hospital as the Hospital Referral Region (HRR).

3.1 Model Assumptions

The method of constructing HRRs assumes that people prioritize proximity over other factors in hospital selection. For the Netherlands, results have been presented for both angioplasty (Varkevisser et al., 2012) and cataract (Ruwaard et al., 2014) interventions, as well as hip replacements (Beukers et al., 2014), to suggest that individuals generally attend whichever hospital is closest to them, with quality indicators playing a secondary role in determining hospital choice. If a large majority of patients in a region determine their hospital choice solely by proximity, spending measures at the local hospital should be reflected in local aggregate hospital expenses.

3.2 Hospital Referral Regions

The method of estimating provider-specific effects from regional trends partly mirrors Wennberg and Gittelsohn (1973), who find that neighbouring communities in Vermont exhibit significantly different utilization of hospital care, dependent on which hospital is closest. Another such study in Virginia on the physician-level (Pai et al., 2000) find that regional variations in health care expenses may be largely explained by physician inefficiency. For sinusitis related claims, the authors find significant cost differences between physicians, amounting up to 48%. Similar studies are summarized in Skinner (2011), who specify the methodology as defining a set of Hospital Referral Regions that contain a subset of the population, where provider efficiency is estimated from the effect of being in a particular HRR. If one health care provider is more efficient than the others, then the areas closest to that provider should show significantly lower health care costs, net of confounding factors. Skinner (2011) notes that a particular weakness of the methodology is the strong assumption of independence between HRRs. As health care expenses may be spatially correlated, the error for the estimation of one HRR will correlate with the errors of nearby HRRs as well. In the Netherlands in particular, we know health care utilization to be spatially correlated per province, as shown by Moura et al. (2018). Any attempts at relating aggregate HCE to HRR membership should therefore control for known regional factors, so as not to confuse a regional effect for a hospital-specific effect.

3.3 Constructing HRRs

Figure 1 illustrates an example of a hospital referral region for a hospital in the province of Overijssel in the Netherlands. The postal code of the hospital is shaded in blue. The areas in green directly bordering the postal code containing the hospital are likely to obtain most of their specialist health care from this particular hospital. Together, they form the HRR. If the particular hospital is able to implement measures to curtail spending, we expect expenses on hospital care in the HRR to trend away from the national trend. For each hospital, we may construct such an HRR. Using data on the aggregate health care expenditures for postal codes contained in the HRR, we may estimate HRR-specific expenditure levels, and

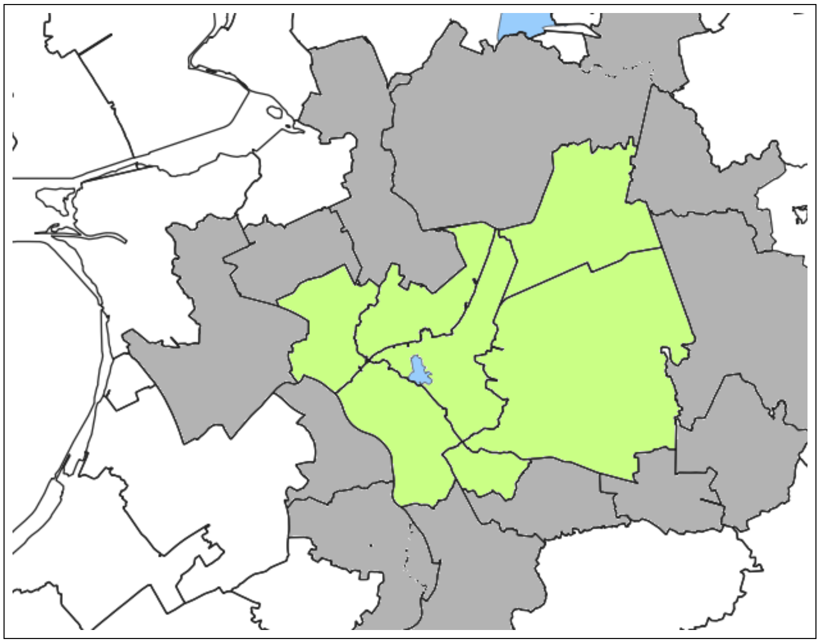


Figure 1: A hospital referral region in the province of Overijssel
■: Control Region ■: Hospital Referral Region
■: Hospital Postal Code

possibly even identify trends. In comparing the HRR-specific trends between hospitals, we may study which hospitals are growing their expenditures in the region, and which hospitals are achieving savings for their HRR. Since hospital choices by patients are likely to rely on travel time, rather than postal code borders or linear distance, we construct the HRRs by proximity in travel time. The exact methodology is described in detail in Section 4.

A practical concern arises when two or more hospitals lie closely together. If it takes a patient 3 minutes to travel to one hospital, and 4 minutes to travel to another, then the assumption of hospital choice being determined solely by the minimal travel time is likely to fail. We therefore limit our analysis to hospitals for which the assumption can be made more confidently, with larger differences between the travel time from the HRR to the hospital and the next-closest hospital. The exact decision rule for exclusion is specified in Section 4.

3.4 Hospital expenditure trends

Once the HRRs are defined, we make the assumption that the individuals living in the HRR make use of that hospital for their hospital care, and all other regions do not. For each region, we know aggregate hospital expenditures for each year of analysis. The overall expenditure trend for the HRR is then given by the person-average annual increase in hospital expenditures for the populations that are part of the HRR. We use aggregate expenditures from all regions outside any HRR to estimate a national trend. To obtain a hospital-specific expenditure trend, we subtract from the trend in the HRR the national trend. The resulting estimate reports the annual change in expenditures for people member to the HRR, net of national expenditure trends. The exact methodology is given in section 5.

3.5 Ex-ante spending levels and HRR-specific trends

We take HRR-specific trends to be, at least in part, the result of measures taken by the hospital to achieve savings on their expenditures. Lower trending hospitals are assumed to have achieved a successful cost-saving measure, whilst higher trending hospitals are taken to be accelerating expenditures beyond national trends, potentially becoming more inefficient. However, it may not be fair to judge all hospitals by their trends in expenditures, without also comparing them by their ex-ante expenditure levels. Any hospital with gross inefficiencies in their care delivery may find it easier to achieve a negative spending trend, than a hospital which is efficient to begin with. We therefore expect the estimated HRR-specific trends to be negatively correlated with ex-ante spending levels. Any hospital with a negative trend over the period analysis, but a significantly positive ex-ante HRR-specific expenditure level may be making easier gains than a hospital with both a negative trend as well as a negative ex-ante expenditure level. In identifying potential frontrunner hospitals for finding valuable administrative expenditure-cutting measures, we should focus on both trends in expenditures, as well as ex-ante HRR expenditure levels.

3.6 Primary Care Substitution Effects

As an efficiency measure, it has been widely recommended for Dutch hospitals to defer part of their provided care to primary care physicians. Better access to primary care may limit hospital readmissions (van Dijk et al., 2013), and procedures are provided at a lower cost with primary care physicians than with specialists (Maes and de Wildt, 2006). For an equal volume of health care, this means that procedures are performed at an overall lower cost, and treatment cost is allocated to primary care expenses, rather than specialist care expenses. We expect HRR-specific trends in hospital care expenses to inversely relate to trends in primary care expenses, if the particular HRR relates to a hospital which has exercised substitution policies.

3.7 Comparator Region

In comparing HRR spending trends to the national average, we may worry that any difference in spending trends in the HRR from the national average is symptomatic of other regional demand-side factors, since there may be unobserved heterogeneous determinants of hospital care demand that set the HRR apart from the rest of the country. To control for this, we may define a control region close to the hospital, but not in the HRR. An example of such a control region is shown in Figure 1, where these areas are shaded in blue. These regions are likely to be more similar to the HRR than most other regions in the country. This allows us to control for local time-variant factors driving health care demand. In this paper, we mainly study hospital-specific effects with national trends as the comparator, appendix B reports results for a similar analysis relative to control regions.

4 Data

4.1 VEKTIS expenditure data

We observe aggregate health care expenditures, specified per gender-age subpopulation of 3-digit postal code areas[1]. Age categories are specific to the exact year. There are a total of 799 3-digit postal code areas observed in our dataset. 96.0% of postal code-specific subpopulations are observed each year. 1.8% has one year missing, 2.2% has more than one year missing. Using the size of each subpopulation in each year, we calculate the hospital and

[1] In the Netherlands, postal codes are given by four numbers and two letters. Any 4-digit postal code area contains the cluster of addresses with the same four-digit start of the postal code. By construction, these will cover a contiguous area. Any 3-digit postal code area contains all such 4-digit postal code areas sharing the first three digits. This is also a contiguous geographic area.

primary care expenditures per capita for each year.

Health care expenditures over the years 2011 to 2017 are given, specified across 24 categories. Since we are interested in the efficiency of hospitals in the Netherlands, we are particularly interested in the category of specialist care expenditures, which is the type of care expenditure that may be attributed to local hospitals. Figure 2 reports total and specialist health care over time. We find that total health care expenditure has grown over the period of analyis from €35.2 billion in 2011 to €42.8 billion in 2017. Expenditures on hospital care have also grown, but at a lesser rate. We particularly note a small decrease in hospital expenditures in the year 2015, contrary to an increase in total expenditures. Hospital expenditures in 2011 amounted to €18.9 billion, increasing to €22.6 billion in 2017. Figure 3 reports hospital expenditures over time for men and women, aggregated across three age categories. We see that hospital expenditures are much higher for the elderly, and lowest for the underage populations. Women have higher expenditures in the age category 19-64 relative to men, whilst men report higher expenditures in the underage and elderly categories. Overall trends in expenditures are similar across the six categories, showing an overall increase over the period 2011-2017 with a dip in the year 2015. The presented figures are total expenditures for the Netherlands. In the same period, per capita pending started at € 1126, increasing to € 1180 in 2012, € 1225 in 2013, and € 1247 in 2014. 2015 saw a decrease to € 1211, followed by increases to € 1303 and € 1316. This means that overall expenditures per person have increased by 16.9% over the period of analysis. To give a scale to the results presented in future sections, a € 11.3 annual expenditure trend represents a trend of 1 % in 2011 expenditure levels.

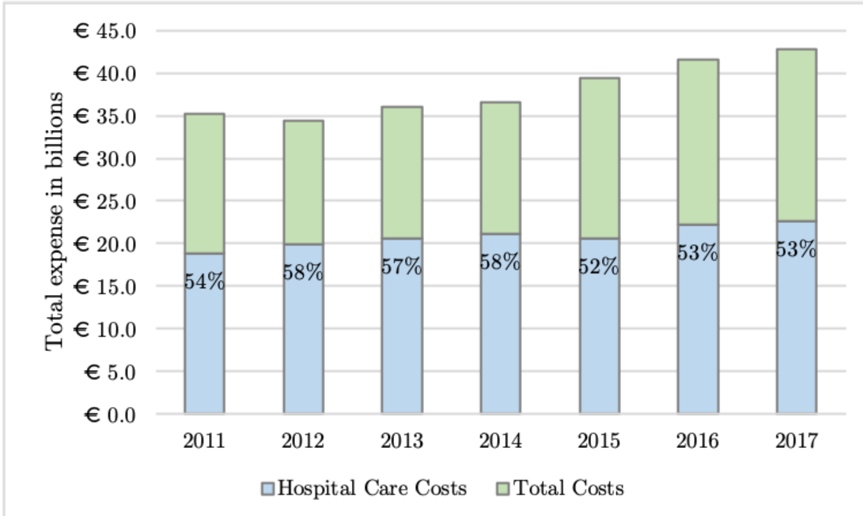


Figure 2: Total- and Specialist Health Care Expenditures over Time

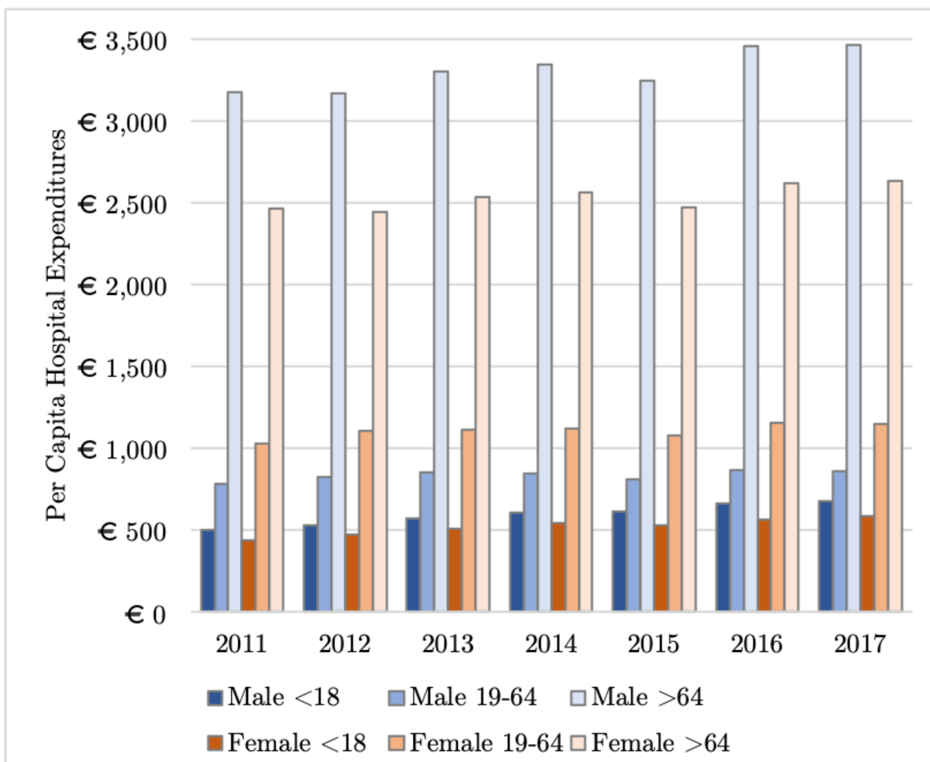


Figure 3: Annual hospital expenditures per age- and gender category

4.2 Hospitals

Hospital location data is obtained from the Dutch National Institute for Public Health and the Environment. The dataset reports 254 hospitals and clinics in the Netherlands by name, address and type of hospital. However, for constructing HRRs we limit ourselves to academic and general hospitals, excluding the smaller outreach clinics, as well as pediatric hospitals. 8 academic hospitals and 105 general hospitals remain.

4.3 Travel Time

We use publicly available travel time data, supplied by Object Vision. Travel times are observed for each possible combination of 4-digit postal codes (PC4) in the Netherlands. Our expenditure data is less detailed and observed at the 3-digit postal code (PC3). Since we know which 4-digit postal codes are contained in each 3-digit postal code, we could take the average over those travel times to obtain the travel time from a 3-digit postal code to a particular hospital. However, we may make the travel time for a particular group of age a and gender g in PC3 area p more exact by taking the weighted average travel time for each of the 4-digit postal codes contained in p, weighing by the age- and gender specific population[2] on the PC4 level, specifically:

$$t_{a,g,p,h} = \frac{\sum^{q \in p} n_{a,g,q} t_{q,h}}{n_{a,g,p}}. \tag{1}$$

a = Age of subpopulation, $a = 1, ..., 90^+$

g = Gender of subpopulation, $g \in \{\text{male}, \text{female}\}$

p = 3-digit postal code, $p \in P$, the set of all 3-digit postal codes, where $|P| = 799$

h = hospital, $h \in H$, the set of all hospitals, where $|H| = 113$

$t_{a,g,p,h}$ = Average travel time in minutes from p to h for people of age a and gender g

q = 4-digit postal code, $q \in Q$, the set of all 4-digit postal codes, where $|Q| = 4070$

$n_{a,g,p}$ = Number of people of age a and gender g in area p

$t_{q,h}$ = Travel time in minutes from q to h

The method described in equation 1 allows us to make the traveltime for a subpop-

[2]Subpopulation sizes are obtained from the Central Bureau of Statistics for years 2011-2016. For the construction of $t_{a,g,p,h}$ subpopulation sizes from 2011 are used. Subpopulation sizes on the PC4 level are reported in 5-year age-bins, rather than specific to the exact age, as in our spending data. We therefore estimate the subpopulation-specific travel times for each 5-year age bin, and assign the travel times to each exact age population a, g, p by their respective age category.

ulation in a PC3 area p more specific than the unweighted average traveltime for p. Since the areas p can be quite large, this may valuably increase the information value of each observation. If a particular subpopulation is quite close to a hospital h, despite the average inhabitant of p being too far away, the subpopulation may still be included in the HRR by virtue of their subpopulation-specific travel time.

Calculating the travel times as in equation 3, we find that the average travel time to the nearest hospital across $\{a, g, p\}$ groups is 14.1 minutes, weighted by population size. The median travel time is 12.6 minutes. The vast majority of the population, 98.3%, live within 30 minutes of a hospital. The maximum travel time to the nearest hospital is 230 minutes, for residents of the island group along the north shore of the Netherlands. Appendix E shows a map of the Netherlands with travel times to the nearest hospital for each PC3 area.

4.4 Constructing HRRs from travel time

Using the travel times for each subpopulation, we may delineate Hospital Referral Regions for each hospital h. Ideally, groups are part of the HRR_h when hospital h is the closest hospital, and other hospitals are a sufficient distance further away, such that travel distance may trump other considerations in hospital choice. To this end, we construct a HRR_h by generating a series of dummy variables D_h, such that:

$$D_{a,g,p,h} = \begin{cases} 1, & \text{if } t_{a,g,p,h} < t_{a,g,p,h^*} + 5, \text{for all } h^* \in H \setminus h, \text{ and } t_{a,g,p,h} < 30 \\ 0, & \text{otherwise, where} \end{cases} \tag{2}$$

$D_{a,g,p,h}$ = Indicator of HRR membership to hospital h for people of age a and gender g living in p.
H = The set of all hospitals

Put explicitly, the HRR consists of all subpopulations for whom the estimated travel time to the hospital is the minimum relative to all other hospitals by a margin of 5 minutes. The travel time should also not exceed 30 minutes, as this may put the subpopulation at too great a distance from the hospital to assume that the hospital is the dominant specialist care provider to the subpopulation.

4.5 Socioeconomic Status

Besides the demographic charcateristics of age and gender, we expect socioeconomic status (SES) to be another important determinant of health care expenditures. In order to perform a fair comparison between hospital referral regions, we include SES as a control variable in our regression analysis. We obtain socio-economic status (SES) scores for each PC4 region from the Netherlands Instute for Social Research. The scores are constructed from average income, the percentage of low-income people in the PC4 area, the percentage of low-educated people in the area, and the percentage of unemployed. The scores are standardised to have a mean of 0 and a standard deviation of 1. Status score data is available for the years 2014, 2016 and 2017. We use the data from 2017 as it is the most complete, limiting the amount of missing observations. 3560 PC4 status scores are reported.

Since we want to model $y_{a,g,p,x}$, we need to make the status scores S_q (q a PC4 area) specific to the populations $\{a, g, p\}$. As in section 4, we make the PC4-codes $\{a, g, p\}$ specific by taking the weighted average of S_q for all $q \in p$, weighing by $n_{a,g,q,2011}$, specifically

$$s_{a,g,p} = \frac{\sum^{q \in p} n_{a,g,q} S_q}{n_{a,g,p}}. \tag{3}$$

a = Age of subpopulation, $a = 1, ..., 90^+$

g = Gender of subpopulation, $g \in \{\text{male}, \text{female}\}$

p = 3-digit postal code, $p \in P$, where $|P| = 799$

q = 4-digit postal code, $q \in Q$, where $|Q| = 3560$

$n_{a,g,p}$ = Number of people of age a and gender g in area p

$s_{a,g,p}$ = Estimated SES score of individuals in subpopulation $\{a, g, p\}$

S_q = Standardized status score for area q.

Since the status score data is incomplete over the set of all existing PC4 regions, we take the weighted average of all remaining PC4 regions for any PC3 regions which are missing a subset of their PC4 regions. The person-average status score per the method above is -0.148. This reflects that lower-status PC4 areas are generally more populated, which causes the person-average score to be below the PC4-average standardized mean of 0. The median score (over individuals) is -0.041, with the 25th and 75th percentiles at -0.639

and 0.455, respectively.

From the scores $s_{a,g,p}$, we construct 5 dummy variables $I_{a,g,p,e}$ that indicate whether the population (a, g, p) is in the e^{th} of 5 quintiles in socioeconomic status, over all people for whom we have an estimated ses score.

5 Methodology

5.1 Estimating HRR-specific effects

To answer research question 1, we estimate HRR-specific trends in per capita hospital expenses, using the model

$$y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \sum_{e=2}^{5}(\delta_e + \theta_e x)I_{a,g,p,e} + \beta_x + \epsilon_{a,g,p,x}, \quad (4)$$

x = year index, $x \in (0, ..., 6)$

$y_{a,g,p,x} = \frac{Y_{a,g,p,x}}{n_{a,g,p,x}}$,Per-capita hospital care expenses derived from the total expense $Y_{a,g,p,x}$ divided by the subpopulation size $n_{a,g,p,x}$

$\gamma_{a,g}$ = Subpopulation fixed effect

H Set of all hospitals, where $|H| = 113$

$D_{a,g,p,h}$Dummy variable denoting membership of population $\{a, g, p\}$ to the HRR of hospital h

α_h = HRR fixed effect

β_x = Year fixed effect

ϕ_h = HRR-specific trend

$\psi_{a,g}$ = Age- and gender-specific trend in spending

$\epsilon_{a,g,p,x}$ = Error term

δ_e = SES quintile-specific effect

θ_e = SES quintile-specific trend

Since we are modelling per capita health expenditures derived from heterogeneously sized subpopulations, we estimate the model as a weighted least squares model, using weights $n_{a,g,p,x}$, where $n_{a,g,p,x}$ is the population in area p of people of age a and gender g in year x.

This allows us to weigh the observations derived from large subpopulations more heavily. As they are less sensitive to statistical noise, the mean spending values from larger populations carry more information value. We are interested in the effect of being in a particular HRR h^* relative to being in no HRR at all. This HRR-specific effect is equal to the change in conditional expectation of the expenditure $y_{a,g,p,x}$ from being in no HRR ($D_{a,g,p,h} = 0, \forall h \in H$) to being in the particular HRR h^* ($D_{a,g,p,h^*} = 1$). As shown in equation 5, this effect is twofold. Firstly, α_{h^*} reports the time-invariant effect of being in the HRR. This reflects the difference in spending level in the HRR relative to the national mean at the start of the period ($x = 0$). A significantly negative α_{h^*} indicates that the HRR has lower spending levels than the national average at $x = 0$. This may reflect lower demand for hospital care in the region, or care being delivered more affordably by hospital h^*. A significantly positive α_{h^*} may reflect the opposite, indicating that demand is higher in the HRR, or that hospital h^* is delivering care more expensively. Secondly, ϕ_h reports the yearly change, or trend, in the difference in expenditures in the HRR relative to the national mean. A significantly negative ϕ_{h*} would indicate that the hospital central to the HRR is in some way curtailing expense growth relative to the national trend. A significantly positive ϕ_{h*} would indicate accelerated expense growth, indicating that the hospital is potentially becoming less efficient or inflating hospital volume in excess of national trends.

$$\begin{aligned} E(y_{a,g,p,x}|D_{a,g,p,h^*} = 1, x) - E(y_{a,g,p,x}|D_{a,g,p,h^*} = 0, x) &= \big(\gamma_{a,g} + \psi_{a,g}x + \alpha_{h^*} + \phi_{h^*}x + \beta_x + \delta_e + \theta_e x\big) \\ &\quad - \big(\gamma_{a,g} + \psi_{a,g}x + \beta_x + \delta_e + \theta_e x\big) \\ &= \alpha_{h^*} + \phi_{h^*}x \end{aligned} \tag{5}$$

We control for the demographic composition of the HRR by adding age- and gender fixed effects $\gamma_{a,g}$, as well as age- and gender specific trends $\psi_{a,g}$. This means that if a HRR is predominantly populated by people of a subpopulation a, g with particularly high spending levels, or a specific trend in spending, this will be factored out in the estimation of the HRR-specific spending level, as well as the HRR-specific trend. We include SES-quantile intercepts δ_e as well as SES-dependent trends θ_e to control for potential correlations between economic composition of the HRR and its spending trends. Economically vulnerable populations may have developments in their health and care expenditures over the period of analysis. To prevent HRR effects adversely substituting economic effects, we control for HRR population SES by including δ_e and θ_e.

To observe the effect these controls have on our estimation, we estimate the model in four forms. First, with $\gamma_{a,g} = 0$ and $\psi_{a,g,} = 0$, as well as $\delta_e = 0$ and $\theta_e = 0$. to observe gross HRR-specific spending parameters. Second, with $\psi_{a,g} = 0$, $\delta_e = 0$ and θ_e to control for subpopulation-specific spending levels. Third, we estimate the model with unrestricted $\psi_{a,g}$. Lastly, we estimate the model with the SES-specific effects included. By observing the changes in the parameters as we build the model from gross differences among HRRs to the model with controls for demographic composition, we can ascertain the influence demographic composition has on the estimation of regional trends.

As described in section 4.4, HRRs include all subpopulations who live within 30 minutes of the particular hospital, and for whom the hospital is the closest hospital by a margin of 5 minutes. This means that anyone member to a HRR is somewhat closely located to a hospital, at least within 30 minutes. The remaining population, which we use as the comparators for estimating our hospital-specific effects, may have travel times anywhere in the range of 0 to more than 200 minutes. If the travel time among the population outside the HRRs is generally higher, we may worry that our estimated HRR-specific effects may include a general proximity effect. For example, if being within 30 minutes of a hospital increases hospital expenditures by a constant amount c, our estimates of α_h may partially be reflecting that constant c, rather than a HRR-specific expenditure level. To control for this, we append the set of hospitals h with a pseudo-HRR for all populations with $t_{a,g,p,h} > 30$ for $\forall h \in H$, such that we also estimate α_{far} and ϕ_{far}. This makes the control group of all people outside the HRR more comparable to our HRR subpopulations, since they will have more similar travel times to the nearest hospital. This means that we may interpret the parameter estimate α_h as reporting the average difference in spending levels over the period of analysis for the HRR surrounding hospital h relative to all other populations within 30 minutes of a hospital, but outside a HRR.

5.2 Primary Care Substitution

Similarly, to answer research question 2, we estimate HRR-specific trends in aggregate primary care expenses, using the model

$$z_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \lambda_h x) + \sum_{e=2}^{5}(\delta_e + \theta_e x)I_{a,g,p,e} + \beta_x + \epsilon_{a,g,p,x}, \qquad (6)$$

$z_{a,g,p,x}$ = Per capita primary care expenses at time x for subpopulation (a,g,h)

λ_h = HRR-specific trend in primary care expenses

The parameters represent the same effects as before, but for trends in primary care expenses. λ reports the HRR-specific trend in primary care expenses. Should we find that a hospital h presents both a significantly negative ϕ_h in (4), as well as a significantly positive λ_h in (6), this may be an indication that the hospital h has made an effort to substitute procedures to primary care physicians. Across the set of hospitals H, if we find the correlation of ϕ_h and λ_h to be negative, this may be an indication that some substitution is partially causing lower hospital-specific expenditure trends, since it suggests that those hospitals with a low expenditure trend are seeing opposite regional trends in primary care expenditures.

5.3 Total Non-Hospital Care Expenses

We may worry that the estimated HRR-specific trends are symptomatic of other regional factors affecting health care demand. To test this, we also estimate the model as in equation 4 for total non-hospital care expenses, which includes all health care expenses across the 24 categories listed, less the hospital expenses $y_{a,g,p,x}$. We estimate the model:

$$u_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \mu_h x) + \sum_{e=2}^{5}(\delta_e + \theta_e x)I_{a,g,p,e} + \beta_x + \epsilon_{a,g,p,x}, \qquad (7)$$

$u_{a,g,p,x}$ = Per capita non-hospital care expenses at time x for subpopulation (a,g,p)

μ_h = HRR-specific trend in non-hospital expenses

If the estimated parameters ϕ_h and μ_h are strongly positively correlated, there may be regional demand-side factors affecting total health care demand, rather than supply-side hospital induced expense trends. For example, if we find both a large positive ϕ_h, as well as a large positive μ_h, then we may have an indication that the reported HRR-specific trend in spending may reflect a growth in total health care demand in the area, rather than a particular failure in curtailing expenditure growth within hospital h. Inversely, if we find a strong negative correlation, non-hospital care may be increasingly substituting for some hospital care in the HRR. If, for example, a particular diagnoses is treated increasingly with a pharmaceutical treatment, rather than an in-hospital treatment, non-hospital care expenditures would increase, whilst hospital care expenditures would decrease.

5.4 Sensitivity Analyses and Extensions

We recognise that the methodology presented in this section relies on key assumptions that may not represent the realities of hospital choice and the subsequent hospital-specific trends in expenditures. To assuage potential concerns with the methodology, and to investigate the estimated hospital-specific effects further, we perform several sensitivity analyses that are further explained in their respective appendices.

First, we perform an estimation in which we change the control group from all people not in an HRR to all neighbours of the HRR within a certain travel time. This analysis may show whether regional effects are being estimated as HRR-specific effects in our initial model, as these regional effects should drop out in a comparison to direct neighbours. The method and results of this sensitivity analysis are reported in appendix B.

Second, we test for the robustness of our results to a change in functional form to a log-linear specification. The methods presented in this section assume nominal yearly trends per HRR. However, it may also be that savings are achieved proportional to previous spending levels, for which a log-linear specification would be better suited. The method and results of this analysis are presented in appendix C.

Third, we assumed a particular method of constructing HRRs in this section that may not accurately reflect hospital choice. Specifically, we assume that HRRs consist of all populations who are within 30 minutes of the hospital and are closest to the particular hospital by at least 5 minutes relative to the next-closest hospital. As a sensitivity analysis, we vary this minimum gap in travel time to test whether the results hold under less stringent, and more stringent assumptions. The method and results of this analysis are presented in appendix D.

We also consider the potential of the methodology for performing event studies on particular hospitals for which we know a policy change has occurred during the period of analysis. We perform such an analysis in appendix A, studying whether two hospitals who have made policy changes to become more efficient show a significantly different spending trend post-treatment. The method to such an event study, as well as the results of the particular example are presented in appendix A.

6 Results

6.1 HRRs

We construct Hospital Referral Regions according to the method described in section 4.4. Figure 4 shows which 3-digit postal codes are included in a HRR. For most postal codes in a HRR, all age- and gender-specific groups are added to the HRR. For a few regions, only part of the population is added due to the group-specific travel times differing sufficiently for groups within the same postal code to fall on either side of the selection criteria in section 4.4. Hospitals in rural areas far away from other hospitals have wider spread HRRs. Hospitals that are not assigned any region to their HRR are typically very close to another hospital, such that for no one in the area they are more than 5 minutes nearer than the second-closest hospital. Figure 5 shows a histogram of the population counts for each HRR in the Netherlands, for the first period of analysis (2011). In the regression analysis in proceeding sections, we limit our analysis to general hospitals with a revenue of 50 to 150 million Euros. This may yield a more fair comparison as it limits potential scale effects on hospital expenditures. Figure 5 also shows the population count for these hospitals only. We find that the population distribution of these hospitals' HRRs is similar to the distribution in the set of all hospitals. Most hospitals have between 45,000 and 158,000 individuals living

Figure 4: PC3-regions by HRR membership

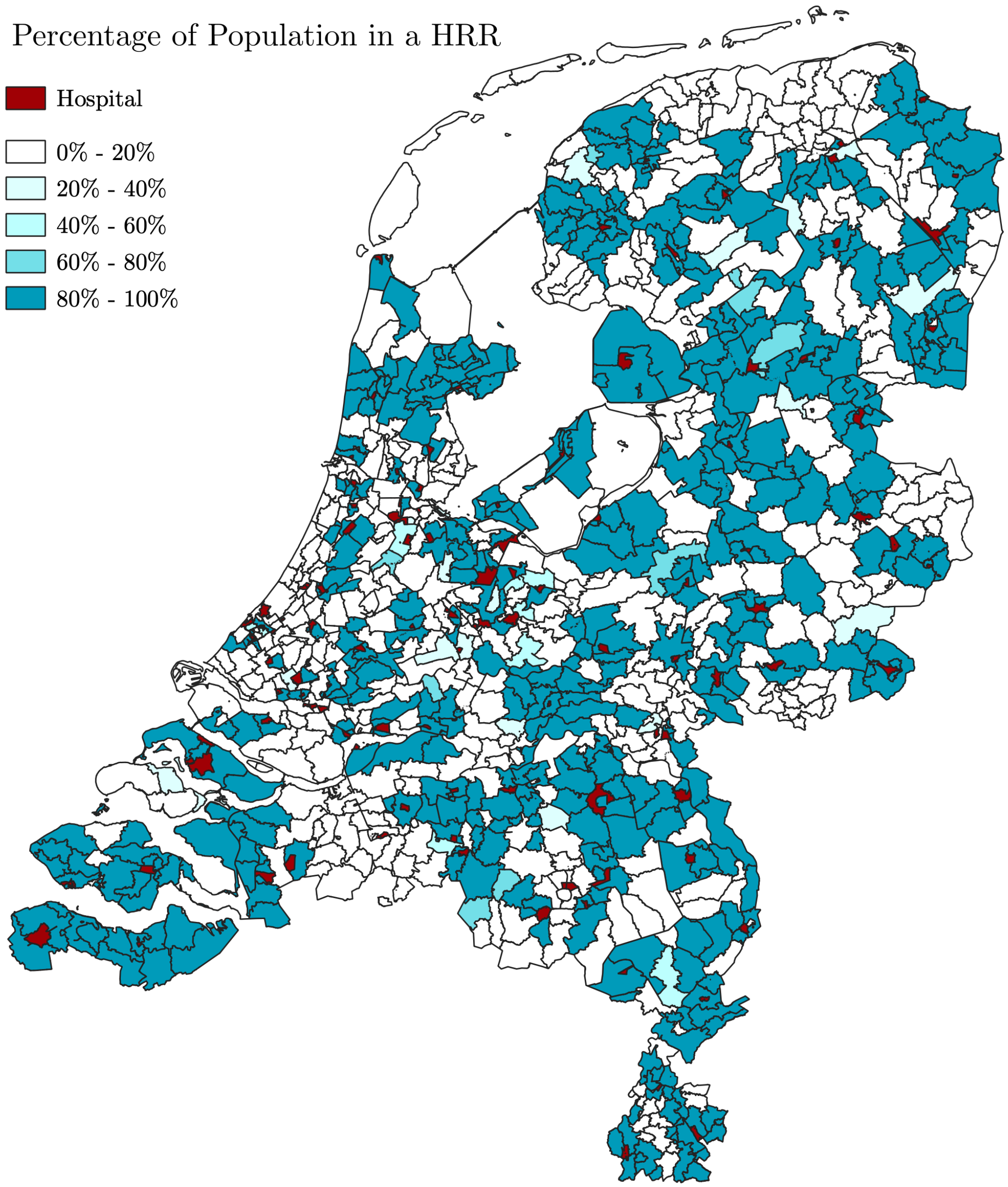
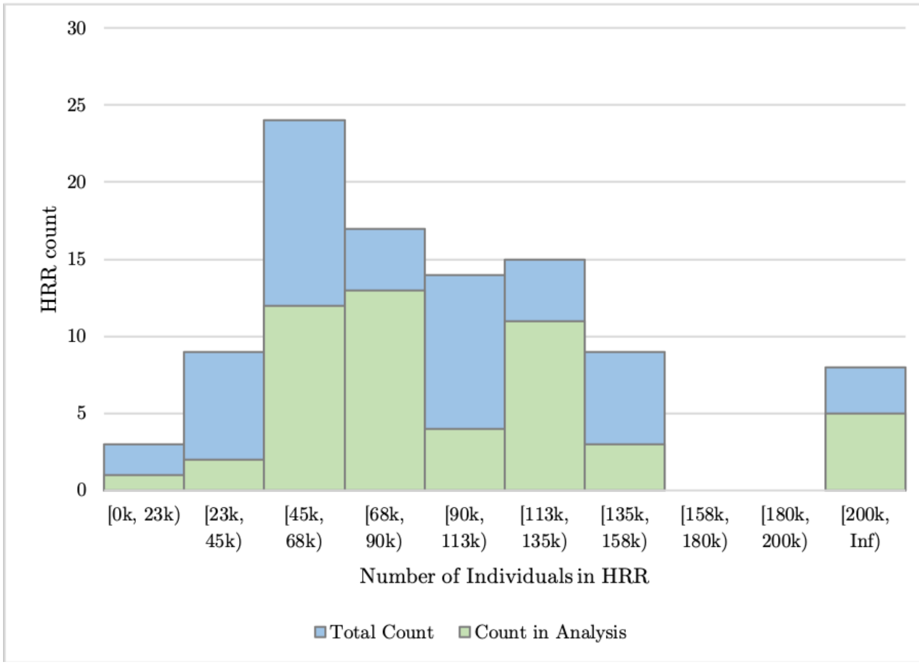


Figure 5: Histogram Populations per HRR



in their HRR. The largest HRRs contain just over 200,000 individuals. These are typically rural hospitals, which have a large HRR as they are the only hospital in their area. 7.73 million people are not in any HRR, of whom 544 thousand are more than 30 minutes away from the nearest hospital. The remaining 7.19 million are less than 30 minutes away from the nearest hospital, but not closest to a particular hospital by a margin of more than 5 minutes.

6.2 Regional Variation in Hospital Spending

We start by observing gross variations in hospital expenditures per PC3 region, as shown in Figure 6. Average per-person hospital spending in 2011 was 1126.89 euro. The standard deviation of the average spending across 3-digit postal codes amounted to 160.64 euro. The lowest average spending in a PC3 area was 37.56 euros per person, which occurred in a low population postal code containing mostly young people. The maximum spending observed was 1646.99 euro in the rural town of Franeker. Higher levels of spending seem to be typical mostly of border regions and cities in the west of the Netherlands. Since these are gross spending levels, uncorrected for age and gender, this may reflect demographic differences across the regions, with the border regions containing a relatively larger elderly population.

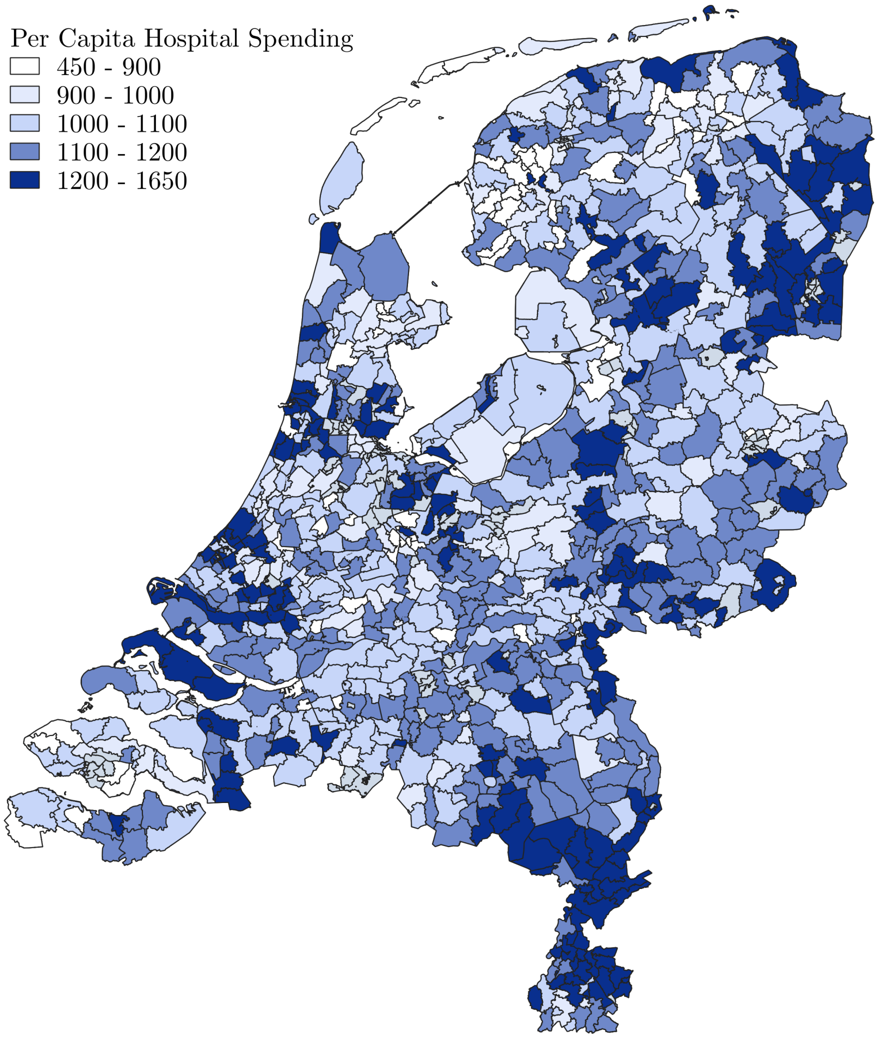


Figure 6: Regional Variations in per-person 2011 Hospital Expenditures

6.2.1 Regression results

We estimate the regression model specified in section 5. The estimated HRR-specific expenditure trends and ex-ante levels are reported in figure 7. Full regression results, including parameter estimates for demographic and economic effects are reported in appendix E. We find significant differences in expenditure trends between HRRs. The hospital achieving the largest year-over-year savings is the Franciscus Gasthuis, which shows a yearly HRR-specific expenditure trend of -29 euro. However, this is offset by an ex-ante spending level of 128.42 euro. This is typical of most hospitals for which we find significantly negative expenditure trends. From visual analysis, we see a clear negative correlation between the ex-ante expenditure level and the estimated trend. This is indicative of a regression to the mean, with savings being most easily achieved by hospitals with gross inefficiencies to begin with. Notable are hospitals such as the 'Onze Lieve Vrouwe Gasthuis', which achieves a negative expenditure trend without showing significantly higher ex-ante expenditures. Such hospitals may have succesfully implemented policies that allow them to go against the national trend of per-patient expenditure increases.

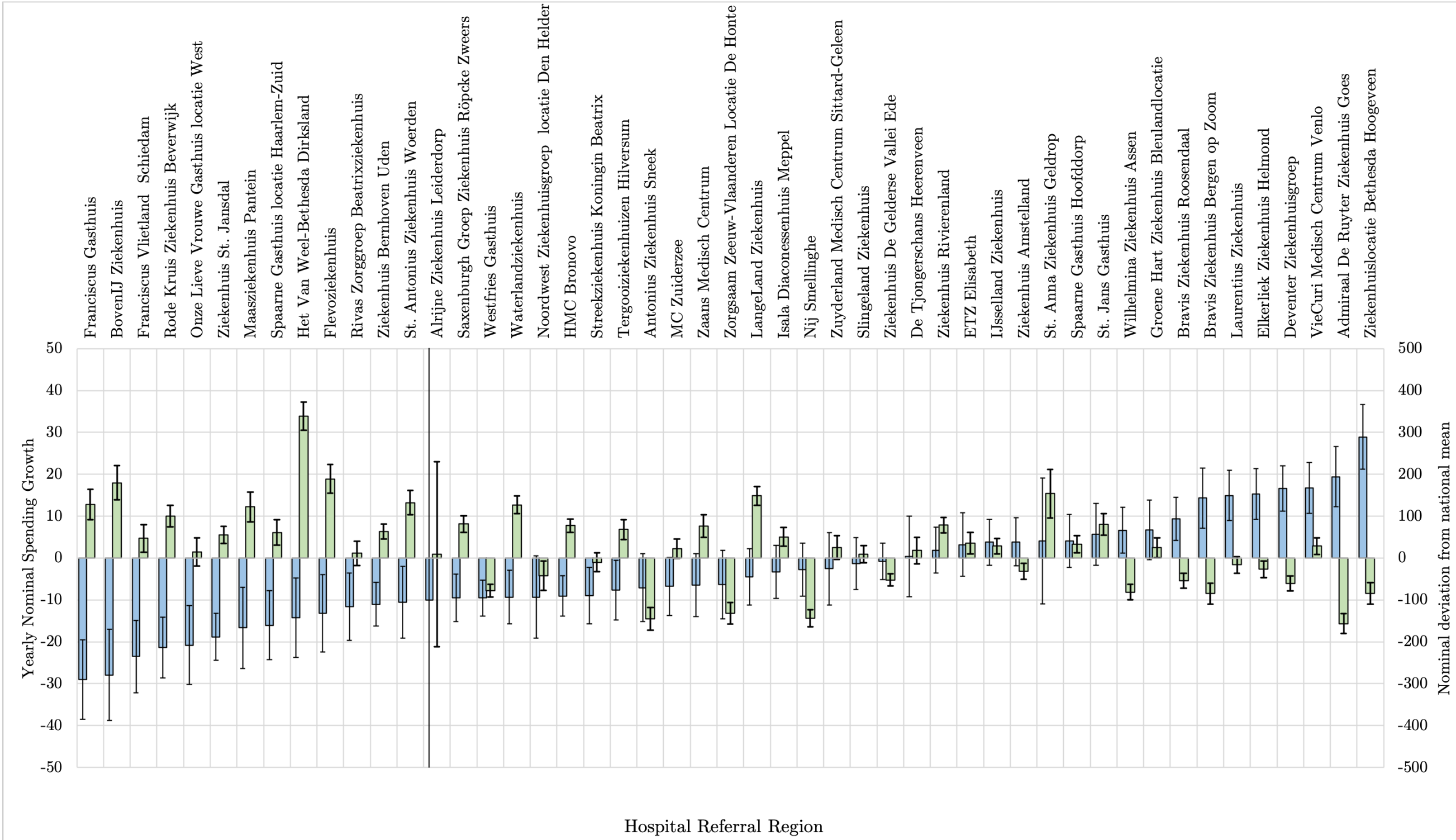


Figure 7: Variations in level and trend per HRR relative to national averages

Figure 7 reports yearly growth of average hospital expenditures in euros by HRR, as well as the ex-ante difference in spending in the HRR relative to the national mean, per the model $y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \sum_{e=2}^{5}(\delta_e + \theta_e x)I_{a,g,p,e} + \beta_x + \epsilon_{a,g,p,x}$, where α_h (the right-side bar) reports the HRR-specific deviation from the mean, and ϕ_h (the left-side bar) the HRR-specific trend. β_x reports the year-fixed effect. The model includes corrections for subpopulation age, gender and socioeconomic status. The error bars give the 95% confidence interval of each estimate.

6.2.2 Comparing levels of analysis

We estimate three different model specifications. First, the gross HRR-specific expenditure trends and levels are estimated, without correcting for demographics and socioeconomic status of each subpopulation. Secondly, we add corrections for demographics, and then thirdly we estimate a model that also corrects for socioeconomic status, per the regression models specified in section 5. To compare these three levels of analysis, figure 8 compares their results by means of a scatter graph. We see that there is quite a large shift in parameter estimates from controlling for age and gender spending levels. Outlying HRR-specific trend estimates are generally reduced in size when adding controls for demographics and SES. Across each level of analysis, we observe a negative correlation between the estimated trend and expenditure level. For gross expenditure trends and levels the correlation is low at -0.04. Once we correct for demographics we find a correlation of -0.48. After correcting for socioeconomics status the correlation shifts slightly to -0.50. Higher expenditure hospitals are more likely to achieve savings over the period of analysis. Hospitals with ex-ante lower expenditure HRRs are more likely to grow their expenditures in excess of national trends. On each level of analysis, we find that being member to a HRR has a significant effect on specialist care expenditures for most HRRs under analysis.

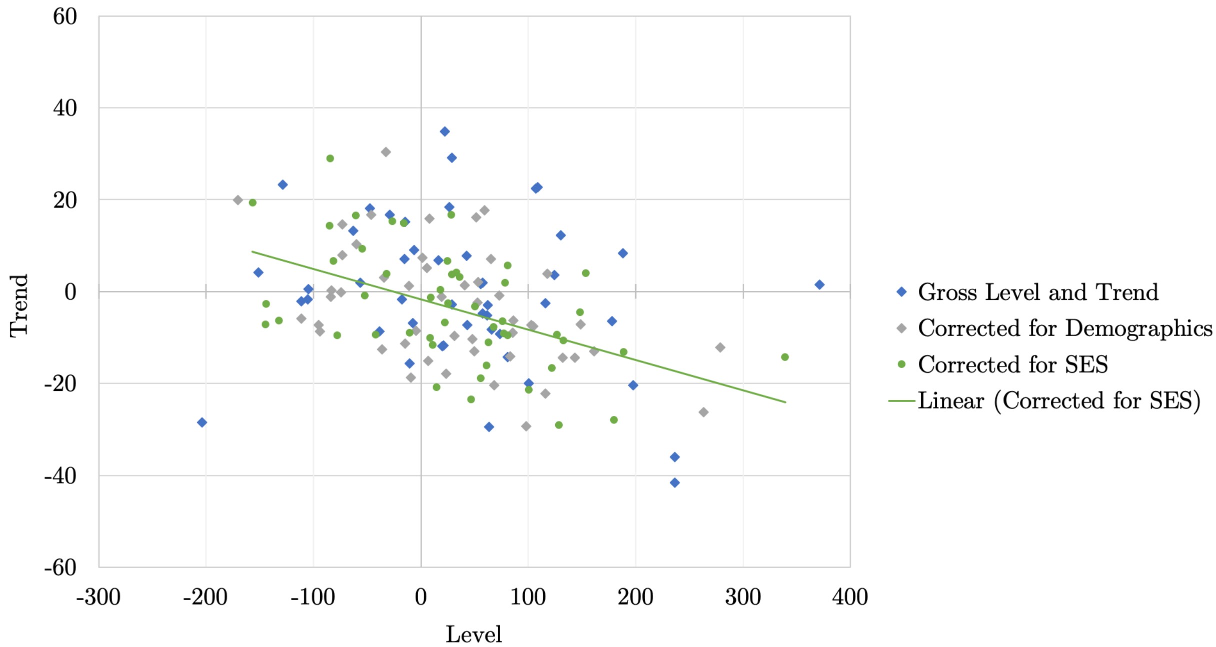


Figure 8: HRR-specific levels and trends per model

Figure 8 shows estimated trend and level parameters for each of three models estimated: Gross levels and trends, levels and trends with age- and gender fixed effects, and a specification with SES-quintile trends and levels.

6.3 Regional Variation in GP Expenditures

Figure 9 reports estimation results from a regression estimating per-capita GP expenditures across HRR regions, including corrections for age, gender and socioeonomic status, as described in equation 6. The scale of GP expenditures is smaller, since primary care is generally much less expensive. Even after controlling for subpopulation-specific levels and trends, we find that GP expenditures are significantly related to the HRR a subpopulation is assigned to. 40 out of 49 HRRs show a significantly different from 0 GP expenditure level, relative to the mean of all other subpopulations not located in a particular HRR. 35 out of 49 HRRs show a significantly different from 0 expenditure trend net of year-fixed effects. The HRRs with lower GP spending trends appear to show higher ex-ante levels. For the HRRs with higher GP spending trends, there seems to be no particular correlation with ex-ante levels.

Figure 10 shows a scatter diagram of the estimated trends in GP expenditures per HRR relative to the trend in hospital expenditures. We include estimations of gross trends, as well as trend estimates after correcting for demographics and SES. We find that in the estimation of gross trends, there is only a small positive correlation between the two estimated trends, which would not suggest the presence of substitution to primary care. After correcting for age and gender levels and SES we still find no strong correlation. Negative trends in hospital expenditures are just as likely to occur in regions with negative trends in primary care, as those with positive trends. We therefore find no conclusive evidence that lower trends in hospital spending may be explained across the board by substitution to the GP, which would cause a positive trend in GP expenditures in HRRs with negative hospital spending trends.

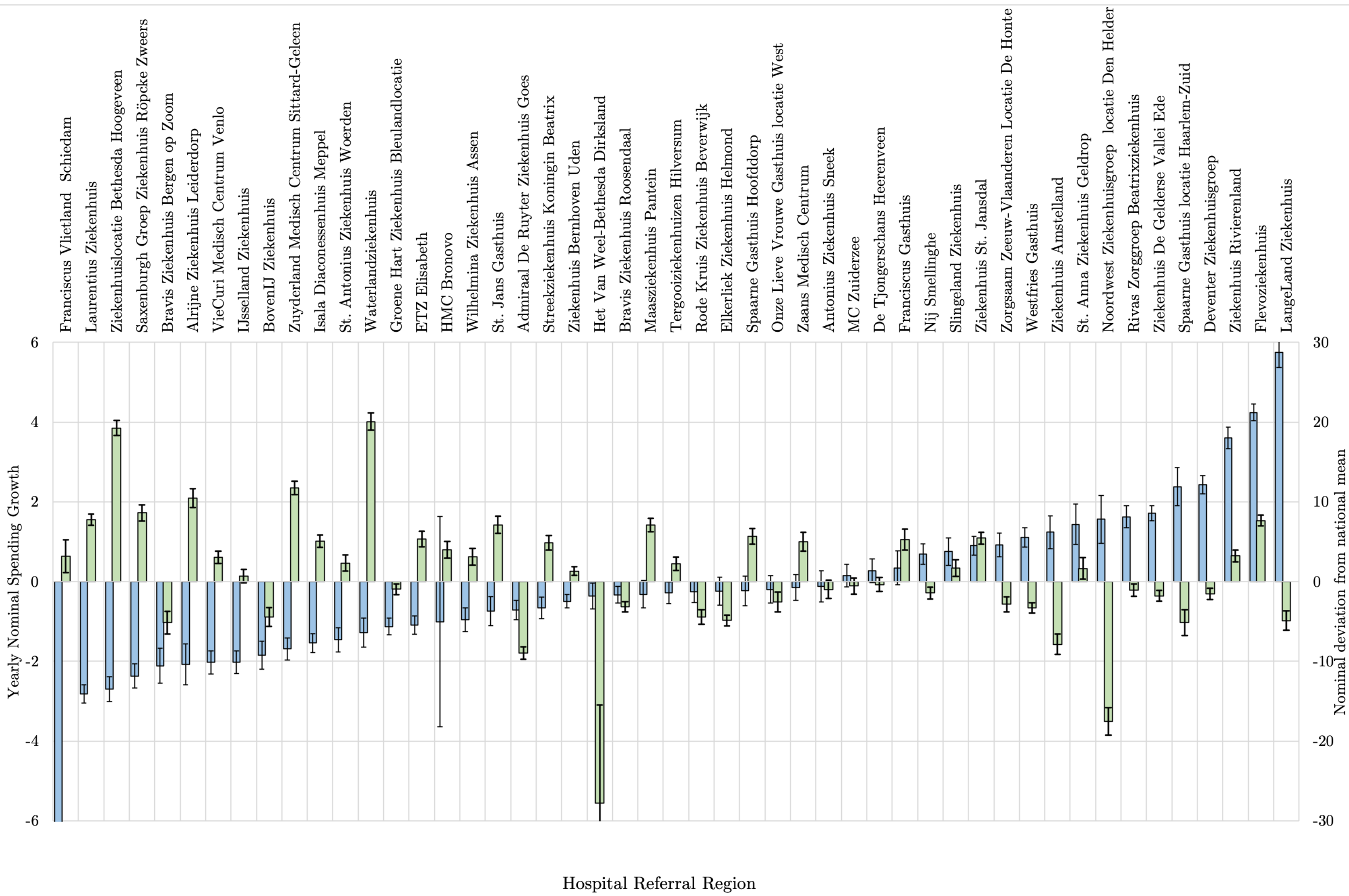


Figure 9: Variations in level and trend for GP expenditures per HRR

Figure 9 reports yearly growth of average GP expenditures in euros by HRR, as well as the ex-ante difference in expenditures in the HRR relative to the national mean, corrected for age and gender, per the model $z_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^H D_{a,g,p,h}(\alpha_h + \lambda_h x) + \beta_x + \epsilon_{a,g,p,x}$, where α reports the HRR-specific deviation from the mean, and λ_h the HRR-specific trend. The error bars give the 95% confidence interval of each estimate. HRR labels also report the shift in ranking by trend relative to the model without age- and gender specific trends.

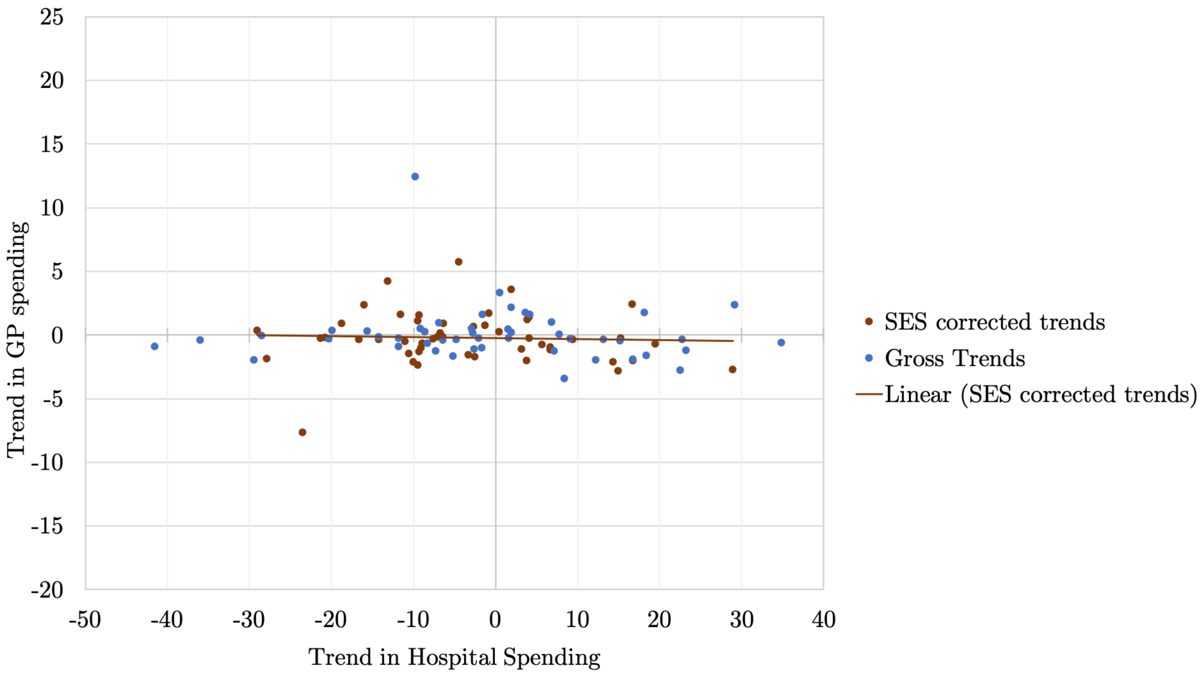


Figure 10: HRR-specific trends in GP vs Hospital Expenditures

6.4 Total Non-Hospital Expenditures

Figure 11 reports yearly trends and ex-ante levels per HRR for non-hospital expenditures. This includes all 23 expenditure categories reported in our dataset that are not directly attributable to the hospital. Categories include GP care, pharmaceutical expenditures, as well as psychiatric and long term care. If estimated HRR-specific effects are symptomatic of regional demand-side factors, we may expect trends and levels in non-hospital care to be strongly related to the trends and levels in hospital care.

We find that non-hospital care expenditures are strongly related to the HRR a subpopulation is assigned. 28 out of 49 HRRs studied report a significantly different from 0 ex-ante deviation from the mean. 15 out of 49 HRRs studied report a significant HRR-specific trend in non-hospital spending. However, the estimated trends seem not to be related to parallel trends in hospital spending. We find large shifts in the relative ranking of trends per hospital. The correlation between estimated trend parameters is 0.04. HRR-specific trends in hospital spending appear not to be symptomatic of an overall growth in demand for health care. Levels of spending between hospital and non-hospital care are slightly positively correlated with a coefficient of 0.35.

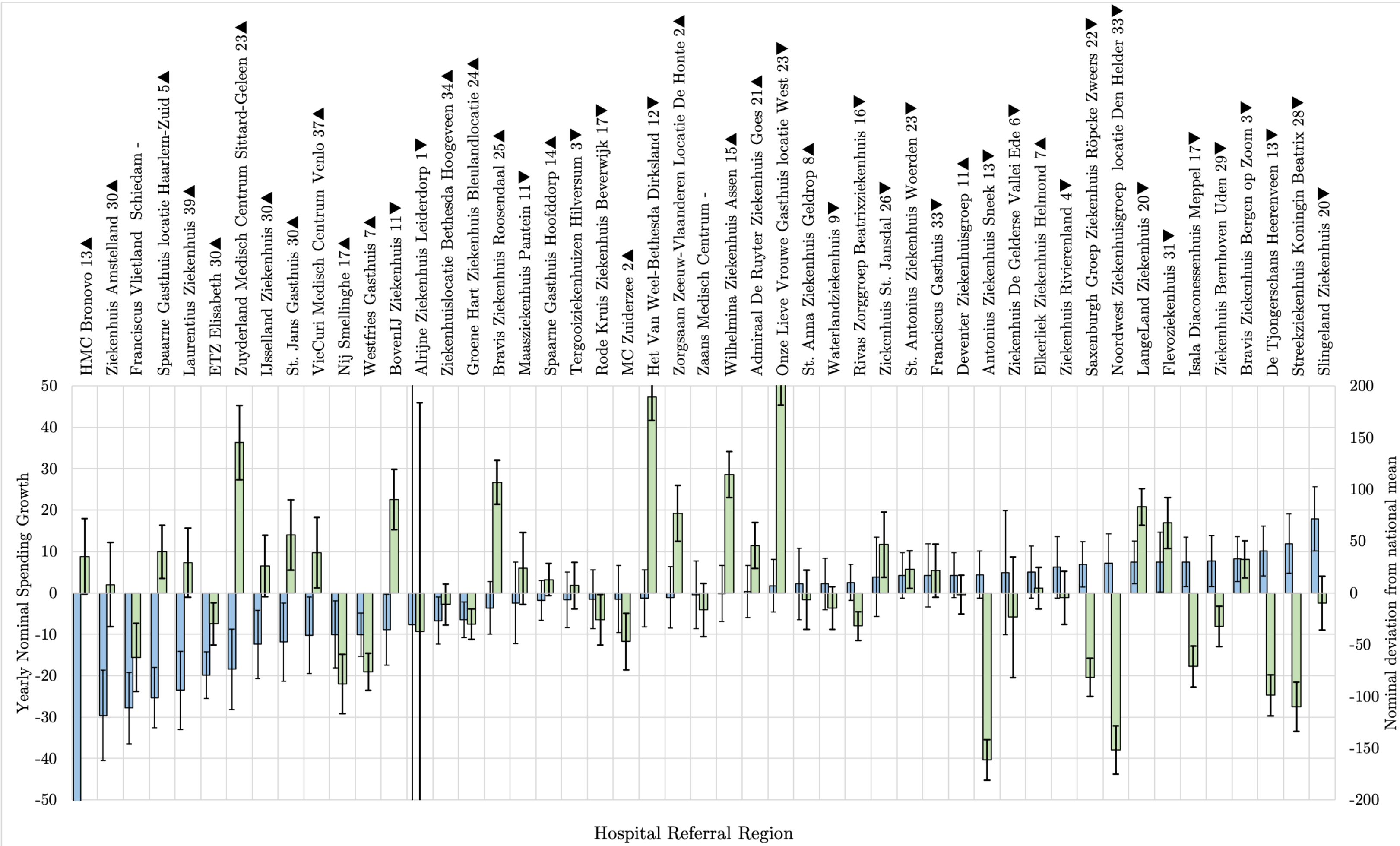


Figure 11: Variations in level and trend for all non-hospital spending per HRR

Figure 11 reports yearly growth of average non-hospital expenditures in euros by HRR, as well as the ex-ante difference in spending in the HRR relative to the national mean, corrected for age and gender, per the model $y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \lambda_h x) + \beta_x + \epsilon_{a,g,p,x}$, where α reports the HRR-specific deviation from the mean, and λ_h the HRR-specific trend. The error bars give the 95% confidence interval of each estimate. HRR labels also report the shift in ranking by trend relative to the model for hospital spending.

6.5 Comparing Best and Worst Performers

Table 1 summarizes regression results and regional characteristics for the 5 hospitals with the lowest spending trend, the 5 hospitals with the highest spending trend, all other hospitals, and the population outside any HRR. We repeat our regression analysis, but group the top 5 hospitals in one HRR, as well as the bottom 5 and remaining hospitals. This gives us group-average parameters α_{bottom}, α_{top},α_{middle}, ϕ_{bottom}, ϕ_{top}, and ϕ_{middle}, comparing expenditures to the same control population as before. We find that in the corrected model, the 5 best performing hospitals have an annual population-weighted average trend of €-24.7, or 2.2% of 2011 average expenditures. Similarly, the worst performing hospitals show a positive trend of €18.4, or 1.6 %. The negative trends appear to be partially offset by higher ex-ante spending levels of €111.9, less so than the positively trending HRRs, for whom we estimate an average level parameter of €-32.6.

The bottom 5 hospitals with a high spending trend see a significant negative trend in primary care expenditures, whilst the top 5 hospitals do not have a significant specific trend in primary care expenditures. This means that we again find no clear evidence of substitution to primary care physicians causing lower hospital expenditure trends, as we would then expect a significant positive primary care trend for the top 5 hospitals.

Non-Hospital spending trends significantly higher for the 5 hospitals with a high spending trend in hospital expenditures, and lower for those 5 with the lowest expenditures trend. This gives some indication that overall healthcare demand, net of age- and gender-specific effects, trends together with hospital care demand, and that the hospital-specific trend may not be fully supply-induced. However, as we saw before, the correlation of the two trends is negative across all hospitals studied, and not very strong.

We also compare regional characteristics of the sets of HRRs. The average age across all regions is similar, as well as gender composition. We note in particularly that the best performing hospitals are in predominantly urban areas. As indicated in the summary statistics, we find that their HRRs have a higher address density, their population receives on average higher government benefits, and a lower proportion of the population is native Dutch. The model already accounts for socioeconomic heterogeneities between HRRs that may drive health care expenditures. Other expenditure differences correlated with these regional characteristics may persist that may not be explained by socioeconomic status or basic demographics. Further modelling of expenditures may be needed to derive whether the HRR-specific trends are symptomatic of regional heterogeneities not caused by the hospital. If this is not the case, efficiency measures in these 5 hospitals can be identified that may explain their trend in expenditures, and potentially be extended to other hospitals as a cost-saving measure.

Table 1: Parameter Estimates and Regional Characteristics by best and worst performing HRRs

Hospital Category	***Bottom 5***	***Middle-of-the-pack***	***Top 5***	***No HRR***
Gross trend	20.27***	- 1.16	-23.06***	-
Gross level	6.28	20.1 ***	38.8 **	-
Corrected trend	18.4 ***	- 3.57***	-24.7 ***	-
Corrected level	-32.6 ***	17.0 ***	111.9 ***	-
Non-Hospital corrected trend	- 1.21	- 2.20***	- 6.83***	-
Non-Hospital corrected level	8.67*	4.28*	- 0.15	-
GP corrected trend	- 0.40***	0.17**	- 2.06	-
GP corrected level	2.91***	1.75***	- 0.75*	-
Age	41.71	41.43	39.67	40.73
Gender	50.0 %	50.6 %	50.3 %	50.5 %
Population (2011-thousands)	536	814	334	7734
Proportion native Dutch	83.2 %	80.5 %	64.8 %	77.7 %
Proportion purchased homes	62.1 %	61.5 %	45.8 %	56.7 %
Mean income category	4.76	5.19	4.76	5.04
Mean government benefits	739.00	770.15	1268.10	819.61
Mean address density	1154	1400	3989	1953

Table 1 reports parameter estimates for trends and levels in hospital spending, for the 5 worst (towards higher expense) trending hospitals, the hospitals with average performance, and for the 5 best performing hospitals, as well as for $\{a, g, p\}$ groups outside any HRR. Both gross and age- and gender-corrected parameter estimates are reported, as well as corrected trends and levels in non-hospital spending and GP spending. The parameter estimates are obtained as described in equation 4 in the methodology section, but regressing on the sum of the dummies for each hospital included in each reported group, rather than the individual dummies themselves. This means that in the paramater estimates above, as well as the descriptive statistics, larger HRRs weigh more heavily by virtue of their regression weights $n_{a,g,p,x}$. Statistical significance is denoted by *** (1%), **(5%) and * (10%). We also report the descriptive statistics "Proportion Native Dutch", "Proportion Purchased Homes", "Mean Income Category" and "Mean Government Benefits" of the HRR regions over each category, obtained from the Central Bureau of Statistics. The statistics are from the year 2015, and supplied at the 4-digit postal code level. They are made {a,g,p} specific per the same methodology to obtain subpopulation-specific travel times, taking the weighted average of PC4-specific statistics using $n_{a,g,q,2011}$.

7 Conclusion

In this paper, we aimed to ascertain whether the national trend towards more expensive hospital care is shared by all hospitals, or whether the trend is driven more so by particular hospitals than others. By observing regional hospital expenditure trends in regions directly surrounding each hospital, we proxy for direct hospital expenditure data by assuming regional trends are at least in part caused by measures taken by the local hospital.

We find that there are significant differences in hospital expenditure trends between the set of Hospital Referral Regions (HRRs) studied. Net of age- and gender effects, the 5 lowest trending hospitals show a trend in expenditures 2.2% below the national trend. The 5 highest trending hospitals show a trend 1.6% above the national trend. We find that the estimated hospital-specific trends can be partially explained by ex-ante spending levels. Hospitals with high ex-ante spending levels are more likely to be able to achieve cost savings than those who started near or below the mean. Estimated HRR-specific expenditure trends and expenditure levels report a correlation coefficient of -0.50. This suggests that the estimated hospital-specific trends may in part represent a regression towards the mean after previous regional shocks in hospital expenditures.

In light of an increased tendency in Dutch healthcare to substitute basic healthcare currently delivered by hospitals to primary care physicians, we studied whether opposite trends in primary care expenditures occur in HRRs with significant trends in hospital expenditures. We find no clear evidence that primary care substitution is causing hospital-specific negative expenditure trends. We find only a slight negative correlation of -0.05 between trends in hospital- and primary care expenditures, and the 5 HRRs showing the highest savings do not show significantly different primary care trends than the average region in our dataset. The estimated HRR-specific trends in hospital expenditures also do not appear to be symptomatic of a general regional trend in health care expenditures. Across the hospitals studied, trends in non-hospital expenditures and trends in hospital expenditures only report a correlation of 0.04.

The top 5 hospital referral regions are more urban than the average hospital studied, with higher address density and a larger immigrant population. Future research may consider whether low HRR-specific trends are typical to larger hospitals as found in urban areas. Although the analysis is limited to hospital with 50 to 150 million euros in annual revenue, some size effects may still occur within this interval.

We find that the estimated trends are robust to changes in the HRR construction algorithm used. Relative rankings of the estimated trends are sensitive to a change in functional form from linear to log-linear, but the sign and magnitude of the estimated trends remain similar. When comparing HRR-specific trends to expenditure trends in the surrounding area rather than to national trends, we find that the estimated sign and magnitude of HRR-specific trends are largely as before, with large changes only occurring when comparing to regions within 30 minutes of the hospital but outside the HRR. Hospital expenditure trends may be caused by other regional factors that may correlate with HRR effects. We include control variables in our methodology for the demographic composition and socioeconomic status of the populations studied. The estimated HRR-specific trends in this model are robust to the addition of the status-specific trends, as well as the addition of age- and gender-specific trends.

The results present in this paper suggest that the national trend towards more expensive specialist care is not shared by every hospital. Some hospitals appear to be accelerating the growth in expenditures, and some appear to significantly limit their expenditure growth. Policy makers may use the established ranking of hospitals by expenditure growth to identify potential frontrunner hospitals in curtailing spending trends.

We note several limitations to the analysis presented in this paper. Firstly, we rely on a quite particular HRR construction algorithm that makes some assumptions on travel time determining hospital choice. The estimated trends may not be fully caused by the single regional hospital, or be relevant not only to the outlined HRR, but larger areas beyond the HRR borders.

Secondly, we control for demand-side factors affecting health care expenditures through age- and gender- effects, as well as socioeconomic status. However, more determinants may be influencing the results. Regional trends in health may be driving expenditures in the HRRs, and more research is needed to establish whether the trends are symptomatic of other demand-side factors, or supply-induced as presumed in this paper.

Thirdly, the established trends suggest significant differences in expenditure trends among hospital. To translate these trends to claims on efficiency gains in certain hospitals requires a quantification of hospital production. Only if the hospital has not sacrificed the quality of its care for achieving savings over the period of analysis should we pursue particular hospitals as potential role models for cost-saving policies.

We urge for further research to investigate trends in quality indicators together with trends in expenditure, and to control more elaborately for potential demand-side factors in determining specialist health care expenditure. We also see potential in applying the method of provider referral regions on other types of health care provider. For any type of health care where people typically use the closest provider, and regional expenditure data is available, the same analysis may be performed.

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Appendices

A Event Study

In this section, we extend on the methods presented so far by considering the HRR framework for studying discrete policy change events. By estimating a discretely time-varying trend parameter for particular hospitals with exogenously known policy changes that may influence the HRR-specific expenditure trend, we may study whether the policy change has proven efficacious in decreasing per-person hospital expenditures. We present an example of such an event study for two hospitals with known policy changes in the years of 2014 and 2013, respectively. The regression model estimated to study structural breaks in HRR-specific trend parameters is given by the equation below.

$$y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + D_{a,g,p,h^*}(\alpha_{h^*} + \phi_{h^*}x + I_{x>t^*}\mu x) + \sum^{H^*} D_{a,g,p,h}(\alpha_{H^*} + \phi_{H^*}x) + \sum_{e=2}^{5}(\delta_e + \theta_e x)I_{a,g,p,e} + \beta_x + \epsilon_{a,g,p,x},$$

h^* = The hospital subject to the event study

$I_{x>t^*}$ = Indicator function that reports whether the event year t^* has passed

μ = Post-event change in HRR-specific trend for h^*

H^* = The set of comparator hospitals specific to hospital h^*

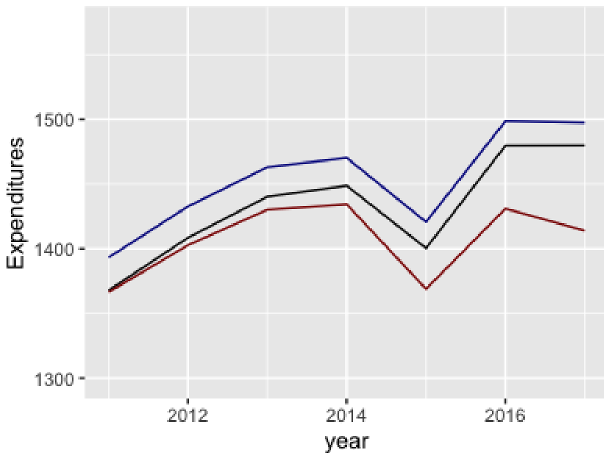
By estimating a post-event structural break in the HRR-specific trend of the hospital of interest h^*, we can test for the significance of a potential change in the expenditure trend for areas surrounding the hospital. Since the analysis considers one hospital separately, we can offset the estimated expenditure trend to a specific set of comparator hospitals H^*. When considering potential size or rurality effects to hospital expenditure levels, this may provide a more fair comparison than the complete set of hospitals across the Netherlands.

The first hospital for whom we estimate the model has seen expenditure measures enacted in the year 2014. We use an exogenously provided set of comparator hospitals for H^* and set $t^* = 2014$. We estimate an HRR-specific expenditure level for h^* of $\alpha_{h^*} = -1.4$, relative to a comparator-average expenditure level of $\alpha_{H^*} = 25.4$. The estimated expenditure trend is $\phi_{h^*} = -4.3$ relative to a comparator trend of $\phi_{H^*} = -1.3$. The estimated trend for h^* changes by $\mu = -12.8$ after the event year (insignificant at the 5 % level). Although the estimated parameter signs and magnitudes are consistent with a successful cost-saving policy, we find no statistically significant evidence of a post-event expenditure reduction.

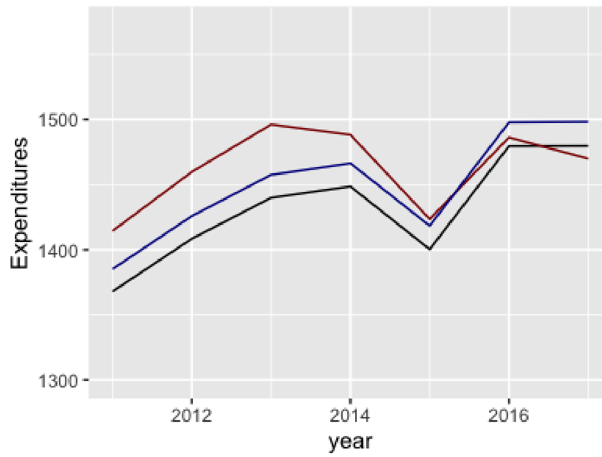
For the second hospital, a different H^* is used, and $t^* = 2013$. We estimate $\alpha_{h^*} = 46.4$, relative to an average expenditure level of $\alpha_{H^*} = 17.2$ for the set of comparator hospitals. The HRR-specific trend for h^* is estimated at $\phi_{h^*} = 4.9$, relative to a trend among the comparators of $\phi_{H^*} = 0.2$. The expenditure trend for h^* is estimated to change by $\mu = -21.4$ (significant at the 5% level) after the event year. This is consistent with a policy change enacted in the event year yielding a significant expenditure decrease in subsequent years.

Figure 12 plots predicted hospital expenditure level s for a male 55-60 year old individual of average SES. For the first hospital, we observe the fitted values in red trending together with the national average in black at first, but find the hospital quickly trending below the average after the event year. The comparator hospitals in blue present expenditure levels consistent with the national average. For the second hospital. we find the HRR is estimated to have higher expenditures in the first period, but ends the period of analysis with lower-than-average expenditure levels relative to both national averages and comparator HRRs.

As shown for the second hospital studied, the HRR method of estimating hospital-specific expenditure trends may also successfully identify the effects of discrete events such as hospital policy changes. In evaluating such measures, the method may be a useful supplement to existing methods of impact evaluation. The results presented in this paper may be usefully extended by future research if data on more hospital expenditure events becomes available.



(a) Hospital 1



(b) Hospital 2

Figure 12: Fitted values among two hospitals with known discrete policy events

B Control Regions

B.1 Model with Control Regions

The model specification in section 5, equation 4 allows for the comparison of expenditure trends in the HRR region with the national average. We take these to be the result of efforts made by the hospital central to the HRR. However, this may be a strong assumption, since the region can be heterogeneous in other unobserved ways that may determine expenditure growth. To control for this, we may estimate the same model as in equation 4, but measuring the HRR-specific trend relative to a local, rather than a national trend. To this end, we define the control region C of a hospital as containing all groups a, g, p for whom the travel time to the hospital is less than T minutes, with $T \in \{30, 45, 60\}$. We perform the analysis iteratively for each hospital, according to the procedure:

foreach $h^* \in H$ **do**
  Discard $y_{a,g,p,x}$ if $t_{a,g,p,h^*} \geq T$
  estimate the model
  $y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^H D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}$,
  weighted by $n_{a,g,p,x}$
end

x = year

$y_{a,g,p,x}$ = Per capita hospital care expenditures in p for population of age a and gender g

α_h = HRR fixed effect

$D_{a,g,p,h}$ = HRR dummy for hospital h and subpopulation (a,g,p)

$\gamma_{a,g,h}$ = Subpopulation fixed effect

β_x = Year fixed effect

ϕ_h = HRR-specific trend

$\epsilon_{a,g,p,x}$ = Error term

t_{a,g,p,h^*} = Travel time for population $\{a, g, p\}$ to hospital h^*

By discarding all observations with a travel time in excess of T, we may interpret the estimated HRR-specific parameters α_h and ϕ_h as reporting the difference in HRR expenditure levels and trends relative to all other subpopulations within T minutes of the hospital, but not in a HRR. This may control for some regional correlations in hospital expenditure, as we no longer compare the potentially heterogenous HRR population to the national mean, but to their direct neighbours just outside the HRR. A significantly negative ϕ_h may indicate that populations member to the HRR are achieving significant specialist care savings in excess of regional trends. This analysis is more robust to regionally correlated demand-side factors, but we run the risk of comparing the expenditure performance of the HRR to a control region that still contains many patients of the particular hospital. Especially in rural regions where hospitals are far apart, control subjects within the travel time T may still have the hospital under analysis as the closest hospital.

We will focus on the difference in estimated HRR-specific trends ϕ_h in the model with control regions relative to the model that takes all populations outside HRRs as the baseline. If the estimated HRR-specific trend persists when comparing with the HRRs direct neighbours, we may infer that they are not symptomatic of regional heterogeneities, and more likely to be a direct result of the hospital's developments in efficiency.

Figures 13 to 15 report the results for $T = 60, 45$ and 30, respectively. Given the size of the Netherlands, most areas within 60 minutes of a particular hospital h still cover a significant part of the country, containing millions of individuals. As we may see in figure 13, the estimated HRR-specific trends relative to this area are quite similar to the estimated trends relative to the national mean. Some shifts in magnitude are reported, but the relative ranking of the trends is largely the same, and shifts in trend size are often within the 95 % confidence interval of the previous estimate. The hospitals with large absolute trends in the previous model mostly still show significant trends relative to the area within 60 minutes drive of the hospital.

Figure 14 shows the same estimation, relative to an area within 45 minutes of the hospital. Again we find the sign and relative ordering of the estimated trends to be largely insensitive to the shift in comparator. Only one hospital out of 49 shows a shift of the estimated trend to outside the 95 % confidence interval of the trend in the model with a full comparator sample. In the results from setting $T = 30$, reported by 15, we see some larger shifts in the estimated trends. Overall, the estimated trends relative to the control region are smaller, with many hospitals now reporting a trend insignificantly different from the expenditure trend in their control region. However, 18 hospitals still report a trend significantly different from their control region. This suggests that whilst for some hospitals the estimated trends may be explained away by regional factors, there is a distinct set of hospitals who influence their regional expenditure growth.

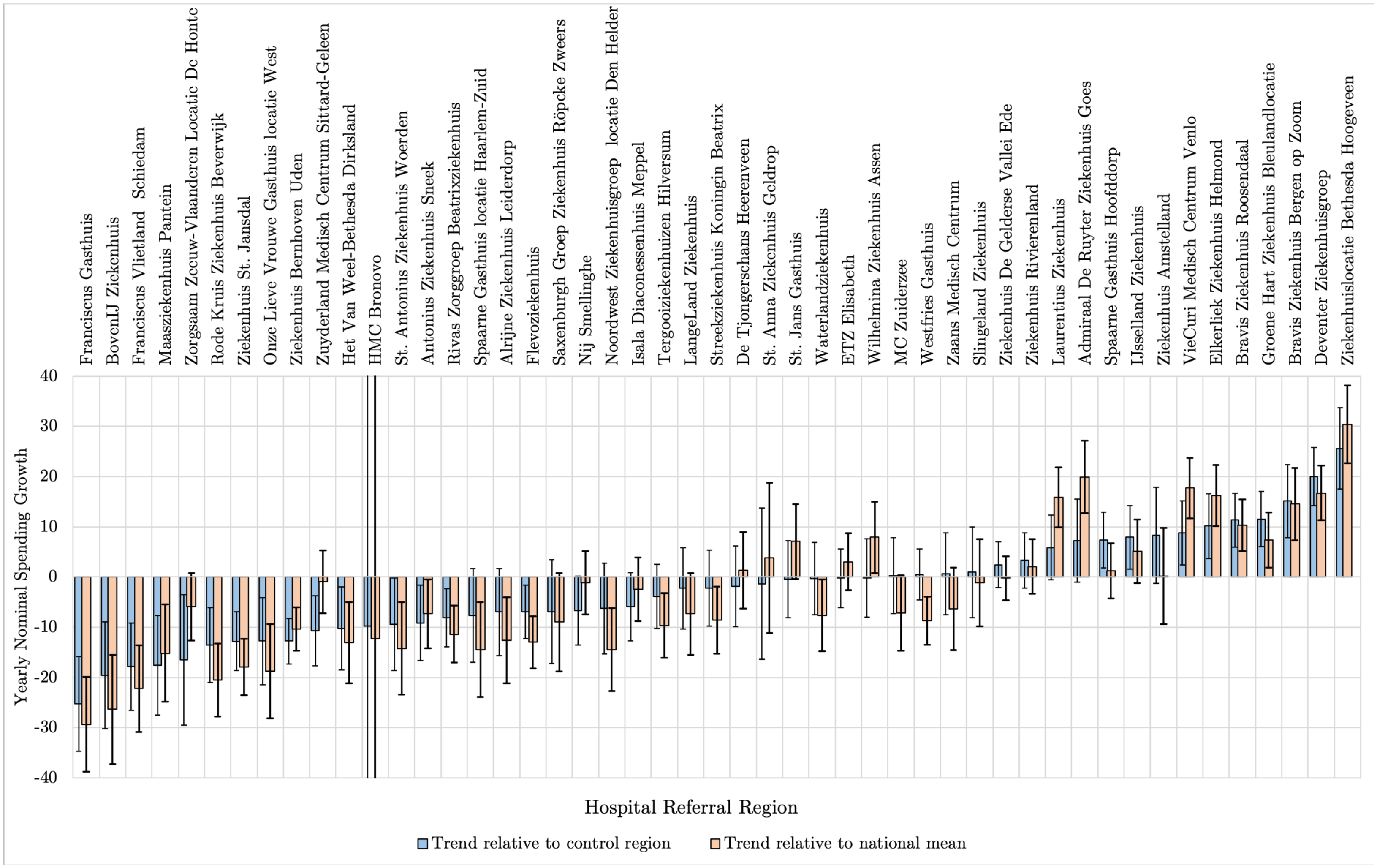


Figure 13: Variations in hospital expenditure trends per HRR relative to a control region, $T = 60$

Figure 13 reports yearly growth of average hospital expenditures in euros by HRR relative to a control region within 60 minutes drive of the hospital, as well as the same trend in hospital expenditure relative to the national mean, corrected for age and gender, per the model $y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^H D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}$, where α reports the HRR-specific deviation from the mean, and ϕ_h the HRR-specific trend. The error bars give the 95% confidence interval of each estimate.

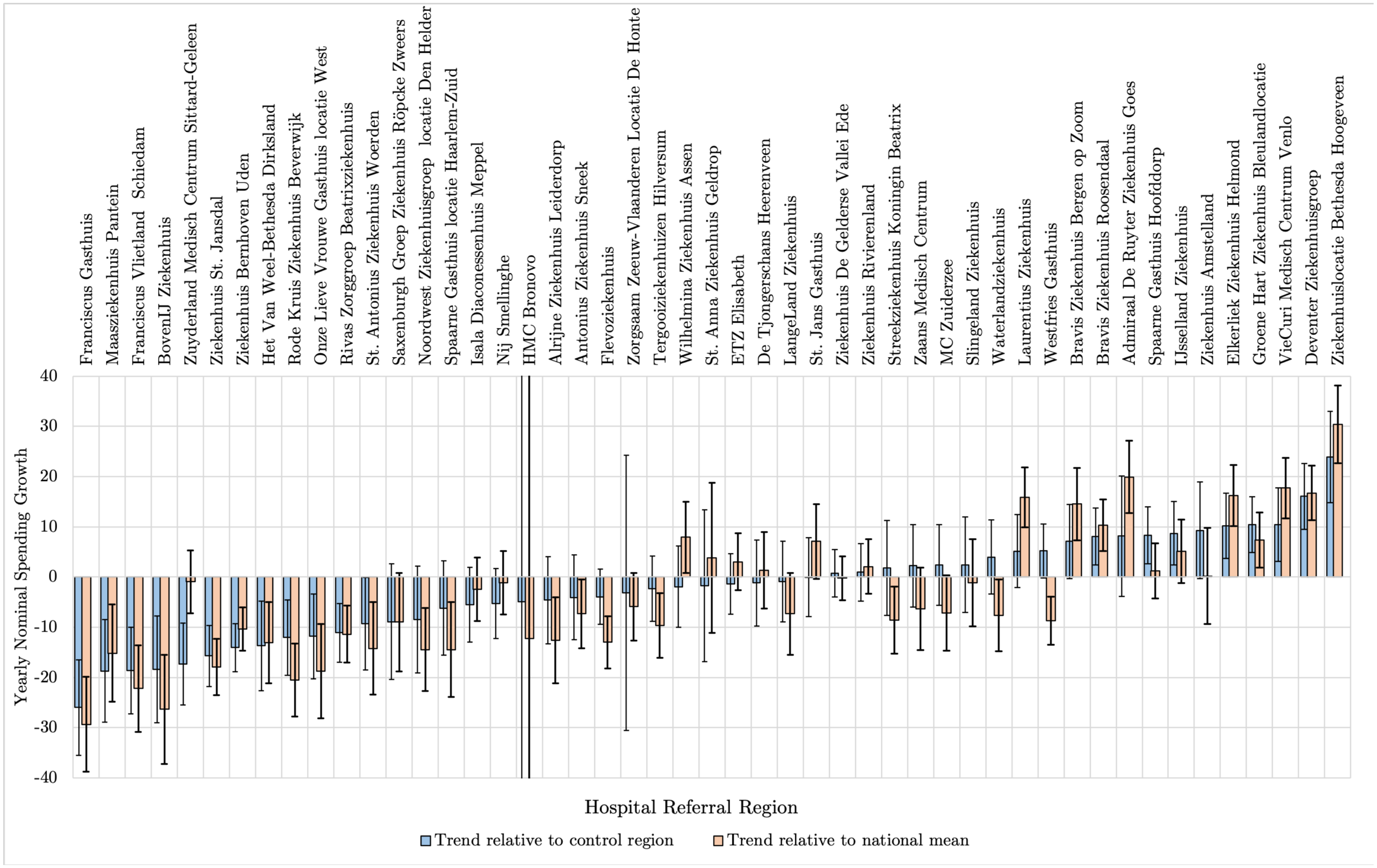


Figure 14: Variations in hospital expenditure trends per HRR relative to a control region, $T = 45$

Figure 14 reports yearly growth of average hospital expenditures in euros by HRR relative to a control region within 45 minutes drive of the hospital, as well as the same trend in hospital expenditure relative to the national mean, corrected for age and gender, per the model $y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}$, where α reports the HRR-specific deviation from the mean, and ϕ_h the HRR-specific trend. The error bars give the 95% confidence interval of each estimate.

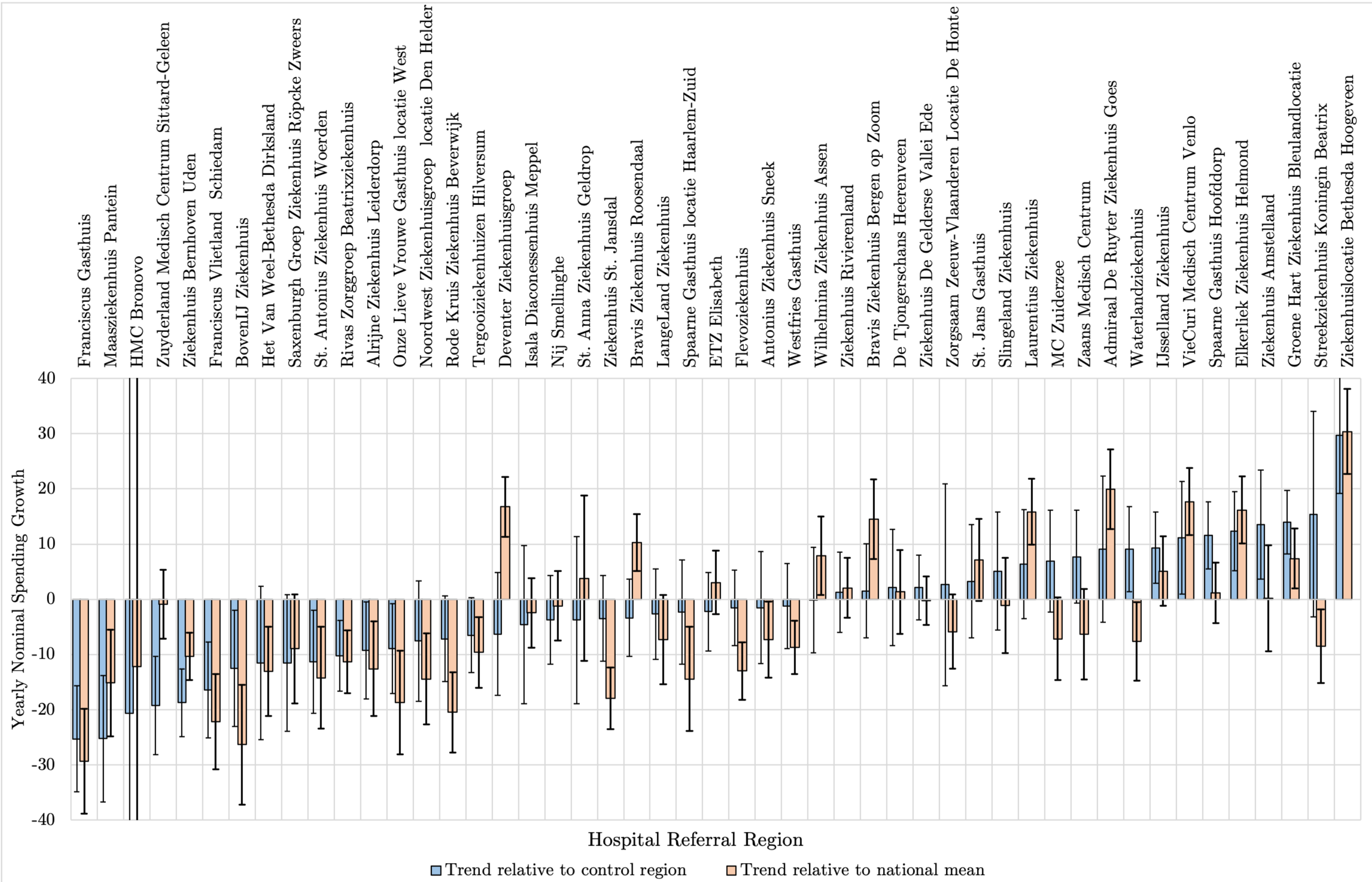


Figure 15: Variations in hospital expenditure trends per HRR relative to a control region, $T = 30$

Figure 15 reports yearly growth of average hospital expenditures in euros by HRR relative to a control region within 30 minutes drive of the hospital, as well as the same trend in hospital expenditure relative to the national mean, corrected for age and gender, per the model $y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}$, where α reports the HRR-specific deviation from the mean, and ϕ_h the HRR-specific trend. The error bars give the 95% confidence interval of each estimate.

C Sensitivity to Functional Form

In modelling spending growth, we have so far assumed a linear functional form. This may misrepresent the economic realities of spending growth, as spending may also grow proportionally over the years. Rather than growing nominally by $(\phi_h + \psi_{a,g})$ euros every year , it may be that hospital spending grows proportionally. To test this, we estimate the log-linear models

$$log(y_{a,g,p,x}) = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}, \tag{8}$$

$log(y_{a,g,h,x})$ = The natural logarithm of per-capita hospital expenditures for population {a,g,h} in year x

$$log(z_{a,g,p,x}) = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \lambda_h x) + \beta_x + \epsilon_{a,g,p,x}, \tag{9}$$

$log(z_{a,g,h,x})$ = The natural logarithm of per-capita GP expenditures for population {a,g,h} in year x

This changes the interpretation of our parameters from nominal to proportional effects. Where $e^{\alpha_{h*}}$ presents the proportional increase in $y_{a,g,h,x}$ from moving from $h = none$ to $h*$, and $e^{\phi_{h*}}$ reports the yearly proportional growth rate particular to the HRR $h*$.

Figure 16 reports the results. 41 HRRs report a significant deviation from the mean at the 5% level, with 32 HRRs reporting a significant HRR-specific trend. We find some shifts in the relative ranking of trends among the HRRs, showing a sensitivity in the relative results to the functional form. These shifts mainly occurr among the HRRs with significant negative trends. The hospital achieving the highest relative savings over the period of analysis is estimated to be the BovenIJ hospital, who show a 2.08% yearly decrease in spending in their HRR. However, we also estimate that their ex-ante spending level was 25.18% above the national mean, indicating that there was significant room for savings to start with. This seems typical to most hospitals showing a significant negative trend. The correlation between the estimated trend and level parameters is -0.42, suggesting that overall, hospitals who achieve savings over the period of analysis were more expensive at the start.

We again find the Bethesda hospital in Hogeveen to have the highest HRR-specific trend, with 2.48% in annual per-capita spending growth.

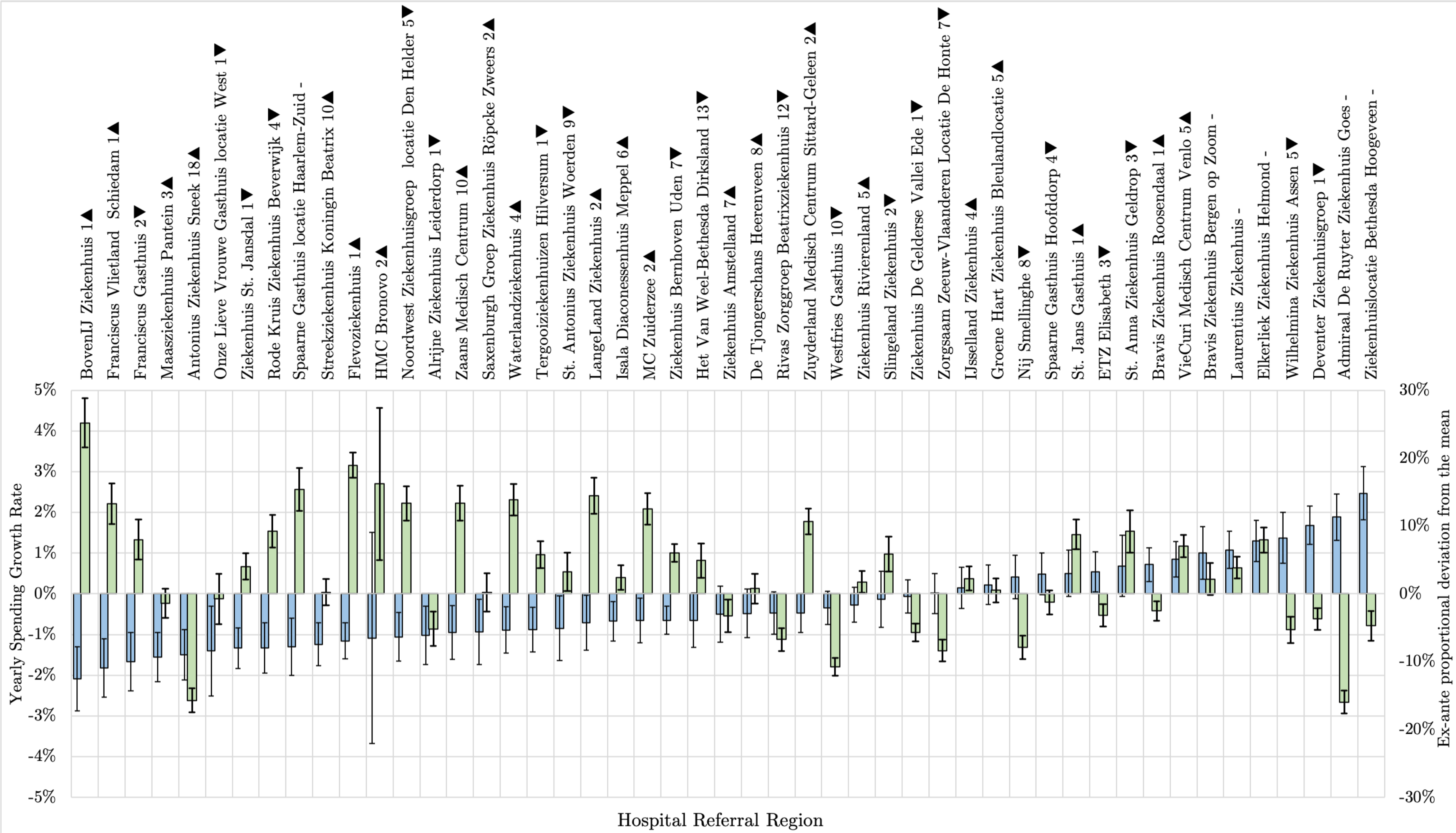


Figure 16: HRR-specific levels and trends in log of spending, corrected for age, gender and age-specific trends

Figure 16 reports yearly growth of average hospital expenditures in euros by HRR, as well as the ex-ante difference in spending in the HRR relative to the national mean, corrected for age and gender, per the model $log(y_{a,g,p,x}) = \gamma_{a,g} + \psi_{a,g}x + \sum^H D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}$, where $e^{\alpha_h} - 1$ (plotted on the right axis) reports the HRR-specific proportional deviation from the mean, and $e^{\phi_h} - 1$ (plotted on the left axis) the HRR-specific trend. The error bars give the 95% confidence interval of each estimate. HRR labels also report the shift in ranking by trend relative to the same model in linear form.

D Sensitivity to HRR construction procedure

We assumed a particular algorithm for constructing HRR regions in section 5, equation 2, which relied on a subpopulation being closest to a particular hospital by a margin of 5 minutes. This margin was chosen as a best guess for what determines hospital choice, and may not be representative of the actual choice heuristics. We therefore generalize to

$$D_{a,g,p,h} = \begin{cases} 1, & \text{if } t_{a,g,p,h} < t_{a,g,p,h^*} + \kappa, \text{for all } h^* \in H \setminus h, \text{ and } t_{a,g,p,h} < 30 \\ 0, & \text{otherwise, where} \end{cases} \tag{10}$$

$\kappa =$ Choice margin in minutes

We re-estimate our most complete models, given by equations 4 and 6 with $\kappa = 3$ and $\kappa = 8$ to test for the sensitivity of our results to the assumptions made in the algorithm.

In constructing HRRs by a gap of 8 minutes, we find that some hospitals that were included in the initial model now drop out due to empty HRRs. 42 out of 49 hospitals remain. A HRR construction algorithm with $\kappa = 8$ is stricter in its construction, and will therefore have a smaller size. The average HRR population (by 2011 data) drops from 94 617 under $\kappa = 5$, to 84 067 average for the hospitals who still have a non-zero HRR population. 32 out of 42 hospitals report a significant HRR-specific level parameter at the 5% level, with 28 hospitals presenting a significant HRR-specific trend. The rank order by trend for most hospitals only shows slight shifts. This suggests that the HRR specific trends in hospital spending are consistent between $\kappa = 8$ and $\kappa = 5$. Figure D reports the estimated level- and trend-parameters.

We may also construct larger HRRs per hospital by setting $\kappa = 3$. This results in a higher number of eligibile hospitals for analysis, since the HRR construction heuristic is less strict for low values of κ. We estimate HRR-specific spending levels and trends for those hospitals also, but they will be left out of the results, since we want to test the sensitivity of our previous results to a change in heuristic. For the 49 hospitals also studied under $\kappa = 5$, the average HRR population under $\kappa = 3$ increases to 112 493. Despite the HRRs having further-reaching borders, which may increase the probability that individuals are assigned to the HRR who attend other hospitals, we find 40 out of 49 hospitals report a significant HRR-specific level, and 32 report a significant HRR-specific trend. Significant differences in hospital spending exist between regions, dependent on which hospital is closest, even when we stretch the boundaries of the HRRs under analysis. Figure D reports the estimated level- and trend parameters.

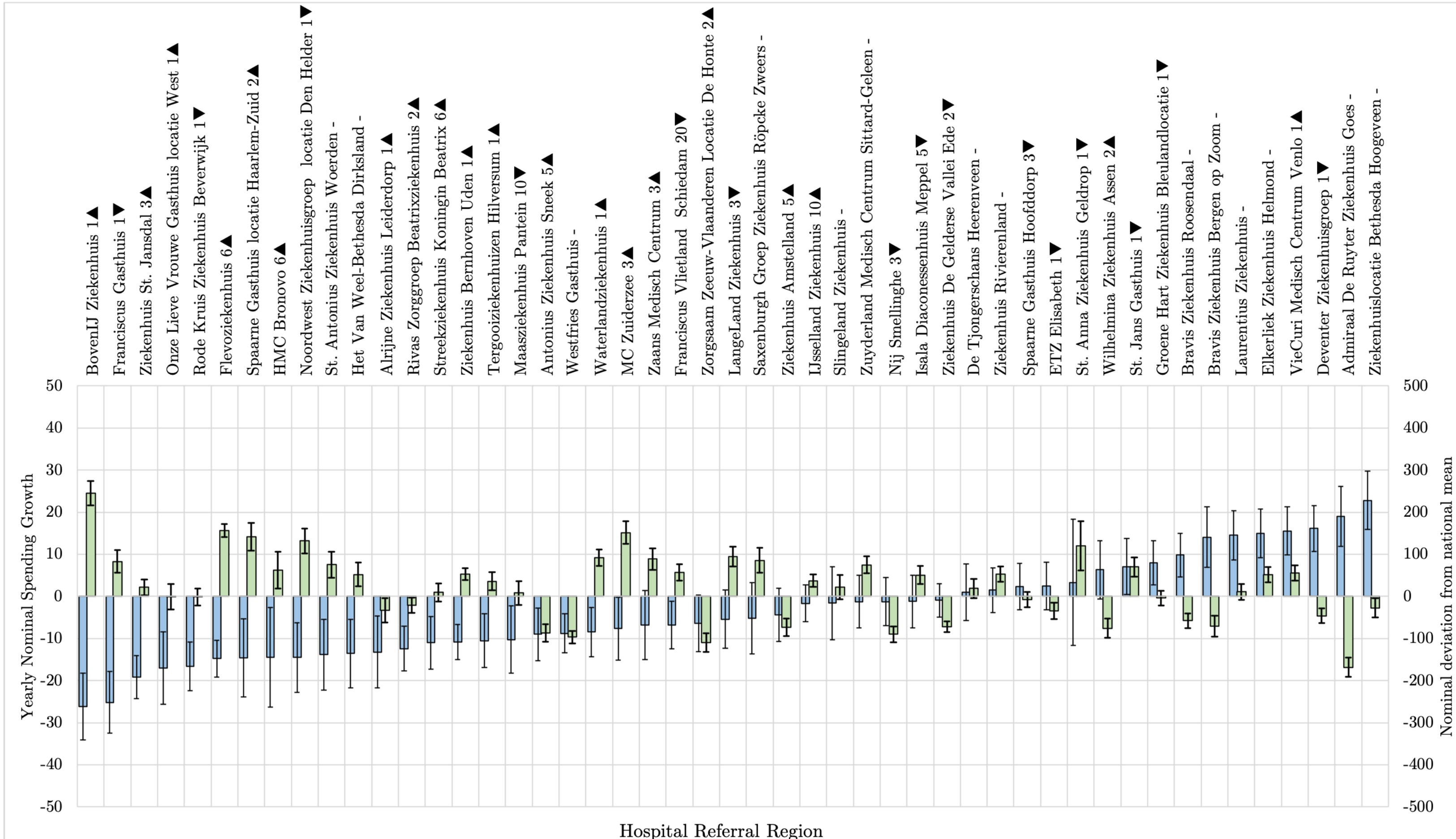


Figure 17: Variations in level and trend per HRR relative to national averages

Figure D reports yearly growth of average hospital expenditures in euros by HRR, as well as the ex-ante difference in spending in the HRR relative to the national mean, corrected for age and gender, per the model $y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}$, where α reports the HRR-specific deviation from the mean, and ϕ_h the HRR-specific trend. The error bars give the 95% confidence interval of each estimate. Populations are added to a HRR if they are closer to that particular hospital by a margin κ of more than 3 minutes, rather than the before-used 5 minutes. HRR labels also report the shift in ranking by trend relative to the model with $\kappa = 5$

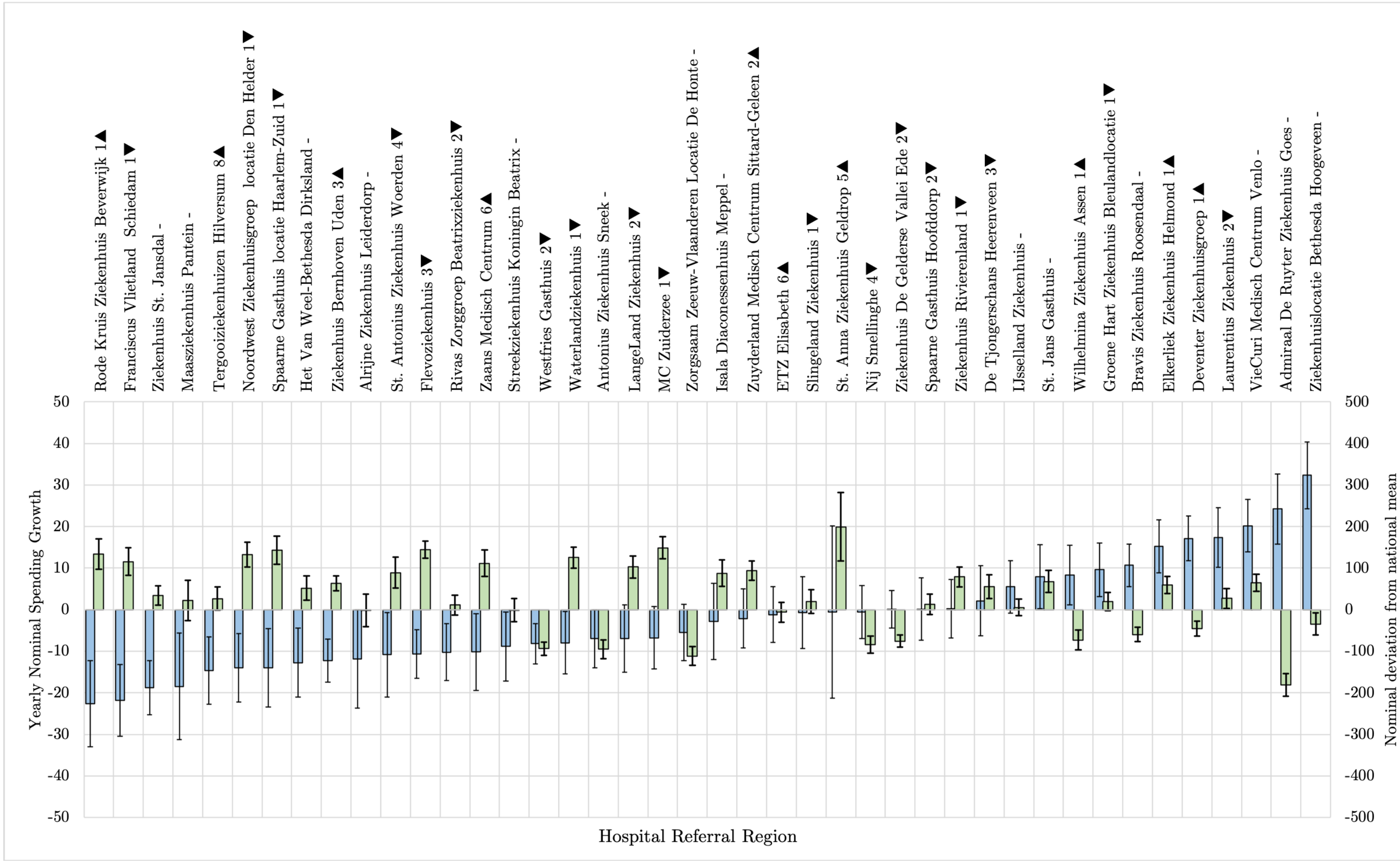


Figure 18: Variations in level and trend per HRR relative to national averages

Figure D reports yearly growth of average hospital expenditures in euros by HRR, as well as the ex-ante difference in spending in the HRR relative to the national mean, corrected for age and gender, per the model $y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}$, where α reports the HRR-specific deviation from the mean, and ϕ_h the HRR-specific trend. The error bars give the 95% confidence interval of each estimate. Populations are added to a HRR if they are closer to that particular hospital by a margin κ of more than 8 minutes, rather than the before-used 5 minutes. HRR labels also report the shift in ranking by trend relative to the model with $\kappa = 5$

E Additional Figures

E.1 Travel times

Figure 19: PC4-regions by travel time to nearest hospital

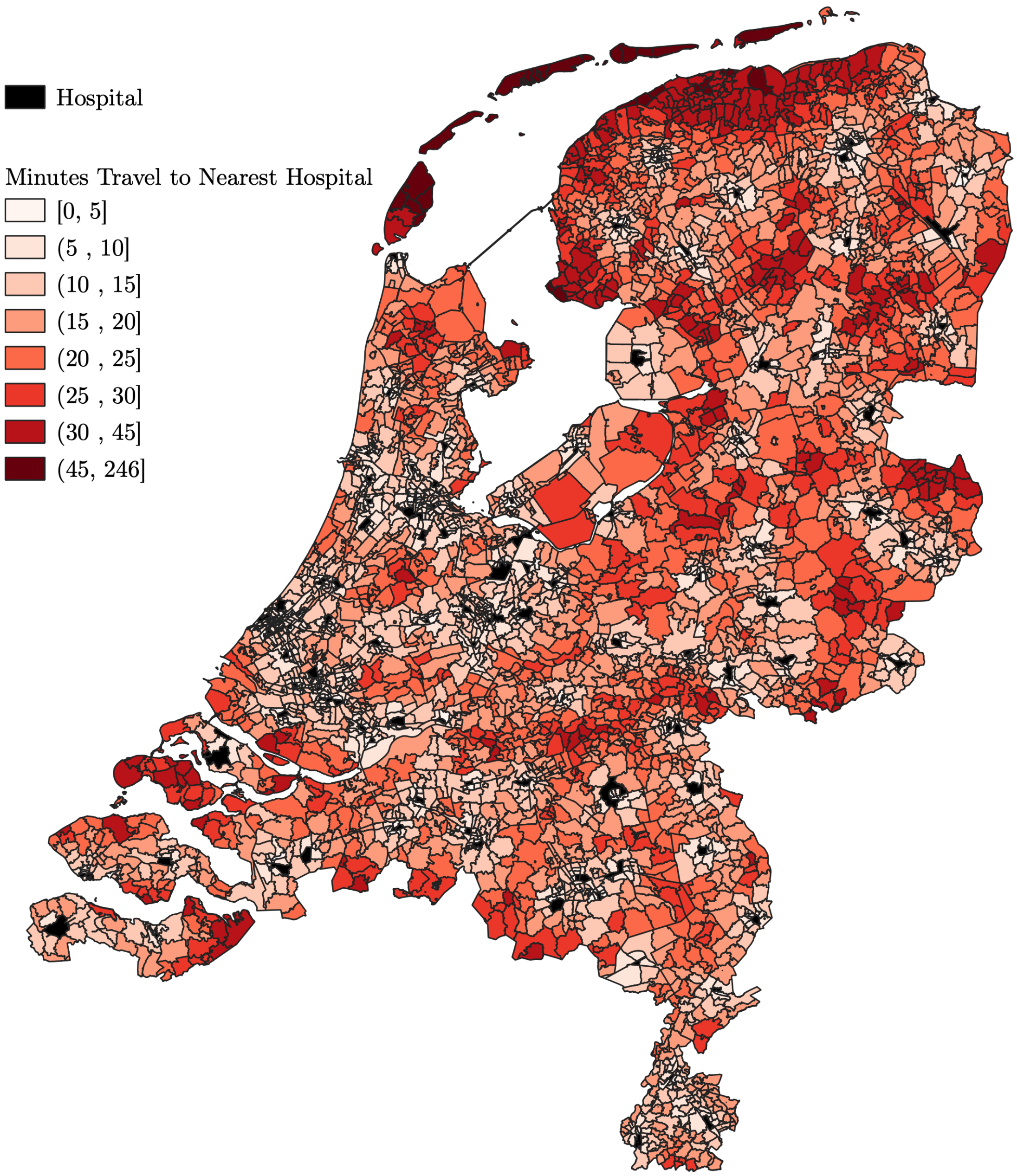


Figure 19 shows all Dutch PC4 areas, categorised by their traveltimes to the nearest general hospital, excluding academic and specialised hospitals.

E.2 HRR-specific gross trends

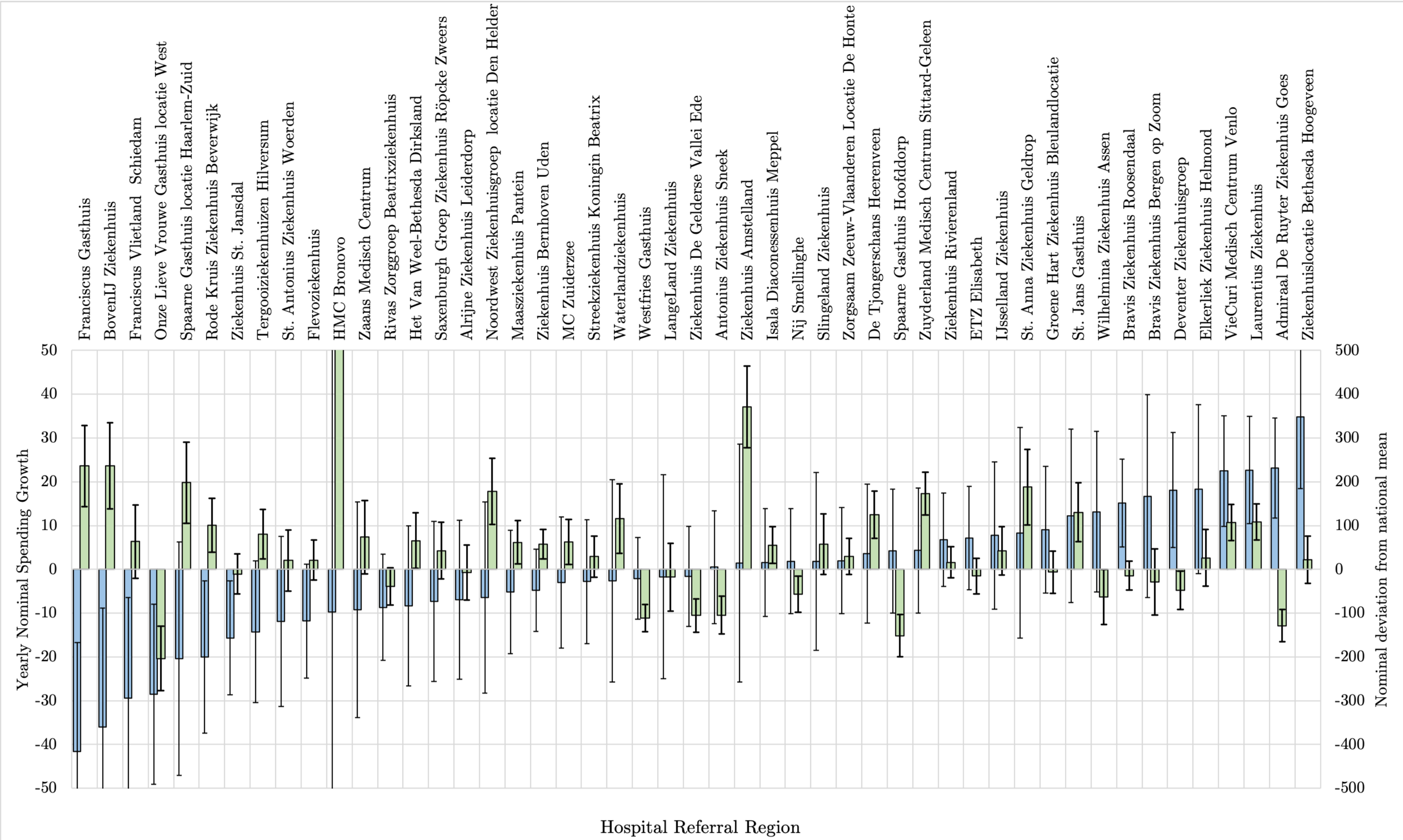


Figure 20: Variations in level and trend per HRR relative to national averages

Figure 20 reports yearly growth of average hospital expenditures in euros by HRR, as well as the ex-ante difference in spending in the HRR relative to the national mean, per the model $y_{a,g,p,x} = \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}$, where α_h (the right-side bar) reports the HRR-specific deviation from the mean, and ϕ_h (the left-side bar) the HRR-specific trend. β_x reports the year-fixed effect. The error bars give the 95% confidence interval of each estimate.

E.3 Age- and gender-corrected HRR trends

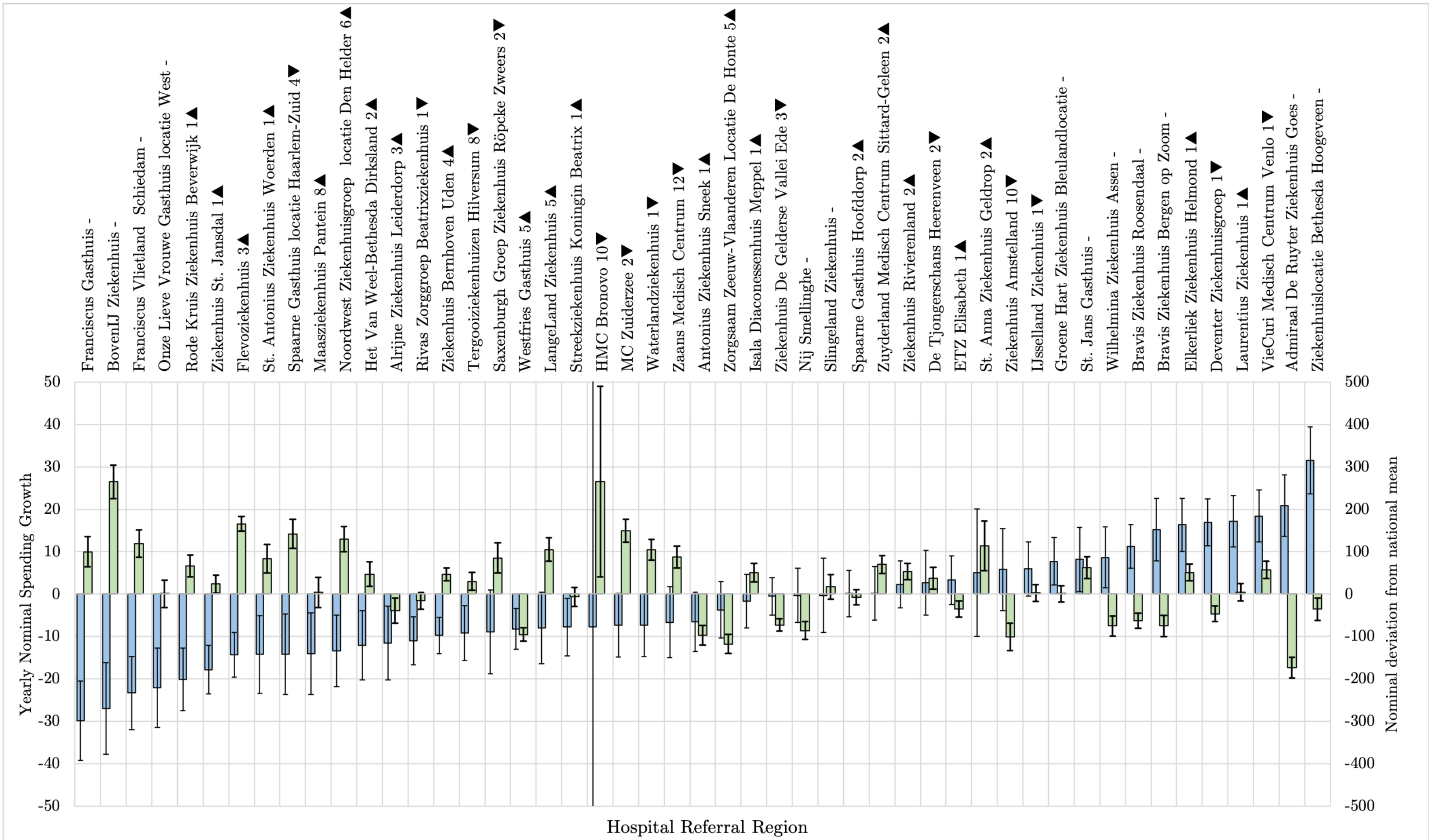


Figure 21: Variations in level and trend per HRR corrected for age and gender

Figure 21 reports yearly growth of average hospital expenditures in euros by HRR, as well as the ex-ante difference in spending in the HRR relative to the national mean, corrected for age and gender, per the model $y_{a,g,p,x} = \gamma_{a,g} + \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \beta_x + \epsilon_{a,g,p,x}$, where α_h reports the HRR-specific deviation from the mean, and ϕ_h the HRR-specific trend. The error bars give the 95% confidence interval of each estimate. HRR labels also report the shift in ranking by trend relative to the model without age- and gender dummies.

E.4 Full regression results primary model

Table 2: Full regression results for HRR-specific expenditures

Hospital/Effect	**Parameter Estimate**	**SE**	**Significance**
(Intercept)	2646.15	27.3	***
HRR-specific intercepts			
Admiraal De Ruyter Ziekenhuis Goes	-156.83	12.2	***
Alrijne Ziekenhuis Leiderdorp	8.82	15.2	***
Antonius Ziekenhuis Sneek	-144.71	12.2	-
BovenIJ Ziekenhuis	179.78	21.5	***
Bravis Ziekenhuis Bergen op Zoom	-85.18	13.5	***
Bravis Ziekenhuis Roosendaal	-54.46	9.1	***
De Tjongerschans Heerenveen	18.27	13.4	***
Deventer Ziekenhuisgroep	-60.88	9.5	-
Elkerliek Ziekenhuis Helmond	35.86	10.5	***
ETZ Elisabeth	-26.65	9.9	***
Flevoziekenhuis	188.90	9.6	**
Franciscus Gasthuis	128.42	18.7	***
Franciscus Vlietland Schiedam	46.75	17.8	***
Groene Hart Ziekenhuis Bleulandlocatie	24.41	9.9	**
Het Van Weel-Bethesda Dirksland	77.37	14.8	*
HMC Bronovo	339.13	112.3	***
IJsselland Ziekenhuis	28.71	10.4	**
Isala Diaconessenhuis Meppel	50.41	11.4	**
LangeLand Ziekenhuis	148.27	14.4	***
Laurentius Ziekenhuis	-16.06	10.2	***
Maasziekenhuis Pantein	22.29	18.4	-
MC Zuiderzee	121.93	14.0	-
Nij Smellinghe	-143.86	10.8	***

Table 2: Full regression results for HRR-specific expenditures

Hospital/Effect	Parameter Estimate	SE	Significance
Noordwest Ziekenhuisgroep locatie Den Helder	-42.11	38.0	***
Onze Lieve Vrouwe Gasthuis locatie West	14.49	17.0	-
Rivas Zorggroep Beatrixziekenhuis	11.12	10.2	-
Rode Kruis Ziekenhuis Beverwijk	100.15	13.5	-
Saxenburgh Groep Ziekenhuis Röpcke Zweers	81.00	18.0	***
Slingeland Ziekenhuis	9.17	15.2	***
Spaarne Gasthuis Hoofddorp	32.96	9.7	-
Spaarne Gasthuis locatie Haarlem-Zuid	61.18	18.0	***
St. Anna Ziekenhuis Geldrop	153.68	29.7	***
St. Antonius Ziekenhuis Woerden	132.38	17.7	***
St. Jans Gasthuis	80.81	13.5	***
Streekziekenhuis Koningin Beatrix	-10.55	11.7	***
Tergooiziekenhuizen Hilversum	67.87	11.0	-
VieCuri Medisch Centrum Venlo	28.30	10.3	***
Waterlandziekenhuis	126.57	13.1	**
Westfries Gasthuis	-78.17	8.2	***
Wilhelmina Ziekenhuis Assen	-81.63	12.7	***
Zaans Medisch Centrum	76.07	13.8	***
Ziekenhuis Amstelland	-31.90	17.1	***
Ziekenhuis Bernhoven Uden	63.10	7.7	.
Ziekenhuis De Gelderse Vallei Ede	-52.24	7.4	***
Ziekenhuis Rivierenland	78.59	9.7	***
Ziekenhuis St. Jansdal	55.66	10.6	***
Ziekenhuislocatie Bethesda Hoogeveen	-84.41	13.5	***
Zorgsaam Zeeuw-Vlaanderen Locatie De Honte	-132.08	11.7	***
HRR-specific trends			
Admiraal De Ruyter Ziekenhuis Goes	19.41	3.7	***

Table 2: Full regression results for HRR-specific expenditures

Hospital/Effect	**Parameter Estimate**	**SE**	**Significance**
Alrijne Ziekenhuis Leiderdorp	-10.07	4.5	*
Antonius Ziekenhuis Sneek	-7.10	3.7	.
BovenIJ Ziekenhuis	-27.93	5.7	***
Bravis Ziekenhuis Bergen op Zoom	14.31	3.9	***
Bravis Ziekenhuis Roosendaal	9.37	2.7	***
De Tjongerschans Heerenveen	0.38	4.0	-
Deventer Ziekenhuisgroep	16.60	2.8	***
Elkerliek Ziekenhuis Helmond	15.27	3.2	***
ETZ Elisabeth	3.17	2.9	-
Flevoziekenhuis	-13.18	2.8	***
Franciscus Gasthuis	-29.07	5.0	***
Franciscus Vlietland Schiedam	-23.52	4.7	***
Groene Hart Ziekenhuis Bleulandlocatie	6.66	2.9	*
Het Van Weel-Bethesda Dirksland	-14.26	4.2	***
HMC Bronovo	-9.10	34.2	-
IJsselland Ziekenhuis	3.77	3.3	-
Isala Diaconessenhuis Meppel	-3.30	3.3	-
LangeLand Ziekenhuis	-4.47	4.3	-
Laurentius Ziekenhuis	14.92	3.1	***
Maasziekenhuis Pantein	-16.68	5.0	***
MC Zuiderzee	-6.79	3.9	.
Nij Smellinghe	-2.73	3.3	-
Noordwest Ziekenhuisgroep locatie Den Helder	-9.34	10.0	-
Onze Lieve Vrouwe Gasthuis locatie West	-20.80	4.8	***
Rivas Zorggroep Beatrixziekenhuis	-11.62	3.0	***
Rode Kruis Ziekenhuis Beverwijk	-21.38	3.8	***
Saxenburgh Groep Ziekenhuis Röpcke Zweers	-9.53	5.1	.

Table 2: Full regression results for HRR-specific expenditures

Hospital/Effect	Parameter Estimate	SE	Significance
Slingeland Ziekenhuis	-1.35	4.6	-
Spaarne Gasthuis Hoofddorp	4.10	2.9	-
Spaarne Gasthuis locatie Haarlem-Zuid	-16.04	5.1	**
St. Anna Ziekenhuis Geldrop	4.07	7.7	-
St. Antonius Ziekenhuis Woerden	-10.60	4.8	*
St. Jans Gasthuis	5.66	3.9	-
Streekziekenhuis Koningin Beatrix	-8.96	3.5	*
Tergooiziekenhuizen Hilversum	-7.67	3.3	*
VieCuri Medisch Centrum Venlo	16.74	3.1	***
Waterlandziekenhuis	-9.34	3.8	*
Westfries Gasthuis	-9.53	2.5	***
Wilhelmina Ziekenhuis Assen	6.62	3.8	.
Zaans Medisch Centrum	-6.48	4.4	-
Ziekenhuis Amstelland	3.84	5.2	-
Ziekenhuis Bernhoven Uden	-11.05	2.2	***
Ziekenhuis De Gelderse Vallei Ede	-0.83	2.3	-
Ziekenhuis Rivierenland	1.87	2.8	-
Ziekenhuis St. Jansdal	-18.83	2.9	***
Ziekenhuislocatie Bethesda Hoogeveen	28.92	4.0	***
Zorgsaam Zeeuw-Vlaanderen Locatie De Honte	-6.35	3.5	.
Zuyderland Medisch Centrum Sittard-Geleen	-2.57	3.2	-
Year-fixed Effects			
2012	167.39	8.0	***
2013	325.82	15.6	***
2014	461.11	23.4	***
2015	539.55	31.1	***
2016	745.45	38.9	***

Table 2: Full regression results for HRR-specific expenditures

Hospital/Effect	**Parameter Estimate**	**SE**	**Significance**
2017	872.28	46.7	***
	Age-group Effects (Relative to 0-year old)		
1 to 5	-2013.55	27.7	***
5 to 10	-2191.26	27.5	***
10 to 15	-2237.75	27.5	***
15 to 20	-2189.67	27.5	***
20 to 25	-2187.45	27.5	***
25 to 30	-2184.05	27.4	***
30 to 35	-2150.18	27.4	***
35 to 40	-2062.43	27.4	***
40 to 45	-1944.01	27.5	***
45 to 50	-1780.56	27.5	***
50 to 55	-1548.68	27.6	***
55 to 60	-1174.72	27.9	***
60 to 65	-746.88	28.2	***
65 to 70	-219.43	28.7	***
70 to 75	393.77	29.3	***
75 to 80	1054.19	30.2	***
80 to 85	1220.23	31.3	***
85 to 90	901.41	33.7	***
90 and older	247.36	37.5	***
	Time-invariant Gender Effect		
Female	-307.82	37.5	***
	SES effects (relative to lowest quintile)		
Quintile 2	73.08	-21.8	***
Quintile 3	106.25	-31.9	***
Quintile 4	117.75	-35.5	***

Table 2: Full regression results for HRR-specific expenditures

Hospital/Effect	Parameter Estimate	SE	Significance
Quintile 5	133.92	-40.6	***
Female-specific age effects			
1 to 5 Female	170.20	38.2	***
5 to 10 Female	222.76	37.8	***
10 to 15 Female	262.32	37.9	***
15 to 20 Female	369.80	37.9	***
20 to 25 Female	519.82	37.9	***
25 to 30 Female	830.08	38.1	***
30 to 35 Female	1000.02	37.9	***
35 to 40 Female	792.78	37.9	***
40 to 45 Female	576.19	37.9	***
45 to 50 Female	508.71	38.0	***
50 to 55 Female	510.31	38.1	***
55 to 60 Female	311.81	38.4	***
60 to 65 Female	118.55	38.7	**
65 to 70 Female	-57.52	39.2	-
70 to 75 Female	-260.98	39.9	***
75 to 80 Female	-540.52	41.0	***
80 to 85 Female	-653.03	41.8	***
85 to 90 Female	-580.63	43.7	***
90 and older Female	-509.18	47.7	***
Gender-specific trend			
Male	41.12	11.2	***
SES-specific trend			
Quintile 2	-1.32	1.0	-
Quintile 3	0.43	1.0	-
Quintile 4	-1.05	1.0	-

Table 2: Full regression results for HRR-specific expenditures

Hospital/Effect	Parameter Estimate	SE	Significance
Quintile 5	-5.23	1.0	***
Age- and Gender-specific trends (relative to 0-year old)			
1 to 5 Female	-118.26	7.9	***
5 to 10 Female	-128.81	7.8	***
10 to 15 Female	-124.70	7.8	***
15 to 20 Female	-129.38	7.8	***
20 to 25 Female	-147.97	7.8	***
25 to 30 Female	-145.03	7.9	***
30 to 35 Female	-130.61	7.8	***
35 to 40 Female	-125.69	7.8	***
40 to 45 Female	-125.15	7.8	***
45 to 50 Female	-123.52	7.8	***
50 to 55 Female	-125.30	7.8	***
55 to 60 Female	-120.08	7.9	***
60 to 65 Female	-106.48	7.9	***
65 to 70 Female	-108.82	8.0	***
70 to 75 Female	-106.76	8.1	***
75 to 80 Female	-117.20	8.2	***
80 to 85 Female	-113.28	8.2	***
85 to 90 Female	-115.93	8.3	***
90 and older Female	-123.06	8.7	***
1 to 5 Male	-153.15	8.2	***
5 to 10 Male	-167.81	8.1	***
10 to 15 Male	-164.46	8.1	***
15 to 20 Male	-164.65	8.1	***
20 to 25 Male	-183.76	8.1	***
25 to 30 Male	-178.82	8.1	***

Table 2: Full regression results for HRR-specific expenditures

Hospital/Effect	**Parameter Estimate**	**SE**	**Significance**
30 to 35 Male	-177.09	8.1	***
35 to 40 Male	-180.06	8.1	***
40 to 45 Male	-176.26	8.1	***
45 to 50 Male	-174.23	8.1	***
50 to 55 Male	-169.57	8.2	***
55 to 60 Male	-167.22	8.2	***
60 to 65 Male	-144.56	8.3	***
65 to 70 Male	-144.82	8.4	***
70 to 75 Male	-127.68	8.6	***
75 to 80 Male	-139.62	8.8	***
80 to 85 Male	-131.34	9.1	***
85 to 90 Male	-121.26	9.7	***
90 and older Male	-139.44	10.6	***

Table 2 reports regressions results for the model $y_{a,g,p,x} = \gamma_{a,g} + \psi_{a,g}x + \sum^{H} D_{a,g,p,h}(\alpha_h + \phi_h x) + \sum_{e=2}^{5}(\delta_e + \theta_e x)I_{a,g,p,e} + \beta_x + \epsilon_{a,g,p,x}$. Parameter estimates, as well as standard errors are presented. Significance is denoted by ***, **, *, and . , reflecting significance at 0.1 %, 1%, 5% and 10 %, respectively.