Long-term returns to local health-care spending

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Abstract

This paper investigates the effects of health-care spending on mortality rates of patients who experienced a heart attack. We relate in-hospital deaths to in-hospital end-of-life spending and post-discharge deaths to post-discharge health-care spending. In our analysis, we use detailed administrative data on individual personal characteristics including comorbidities, information about the type of medical treatment and information about health-care expenses at the regional level. To account for potential selectivity in the region of health-care treatment we compare local patients with visitors and stayers with recent movers from a different region. We find that in regions with higher health-care spending mortality after heart attacks is substantially lower. From this we conclude that there are long-term returns to local health-care spending.

Keywords: Health-care spending, heart attack, mortality, duration models

JEL-codes: C41, H75, I11, I18

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1 Introduction

Regional variations in health-care spending are often associated with regional differences in health outcomes, negatively or positively. The negative association may reflect a causal relationship from health-care expenditures to outcomes, a positive correlation may be driven by the underlying health status of regional population, i.e. unhealthier populations require more health-care spending. It is also possible that there is no observable association because both effects cancel each other out. Our paper investigates whether there is a causal effect of health-care spending on health outcomes. We measure health-care spending at the regional level and health outcomes at the level of individual patients. In order to establish a causal relation we have to take into account various other determinants of health outcomes: individual characteristics like age, gender, health status and unobserved individual characteristics such as vulnerability to certain health shocks. Furthermore, we have to take into account that the choice of patients for certain hospitals may affect their health outcome. Finally, we have to account for possible reverse causality, i.e., regions with an unhealthy population spend more on health care. To rule out that the choice of patients for specific hospitals influences health outcomes we focus on heart attacks, i.e. acute myocardial infarctions (AMI).[1] Individuals who suffer from a heart attack need urgent health care quickly and will therefore be taken to the nearest hospital. Our individual level data provide information about mortality in hospital and mortality after being discharged from the hospital and information about in-hospital and post-discharge health-care costs.

We study how mortality related to heart attacks is affected by both in-hospital and post-discharge health-care spending.[2] To account for potential reverse causality we compare heart attacks of locals – patients who were hospitalized in their

[1] Heart attacks occur when there is a blockage in the supply of blood to the heart causing the heart muscle to receive insufficient oxygen. The blockage is typically caused by a blood clot. Reperfusion – restoration of the blood flow to the heart – is urgent. Blood clots can be broken down by pharmacological means or angioplasty where a catheter balloon is inflated inside the blocked coronary artery.

[2] Health care is expensive. Despite a slowdown following the recessions in 2008 and 2013, annual per capita health spending growth across the Organization for Economic Co-operation and Development (OECD) countries has been around 2.4%. In absolute terms, this translates to an overall average for all member countries of around $4,000. Over the same period, the 30-day mortality rates for AMI decreased from 12.5% to 9.1% in OECD countries (OECD (2021)).

region of residence – and heart attacks of visitors, i.e. patients who were hospitalized in a different region because they visited that area when they experienced a heart attack (see Doyle (2011) for a similar approach). Using information on visitors as part of our identification strategy is appealing. Local populations may represent a selective sample due to the fact that local-area health-care spending reflects the underlying observed and unobserved health status of the inhabitants. To estimate causal effects of post-discharge spending, we use information on patients migrating between regions before they experienced a heart attack. Several studies document the relationship between higher treatment costs and mortality, suggesting that patients in worse health require more intense treatments. Even though the risk factors for heart attacks are relatively well-known, their occurrence is not foreseeable. Heart attacks represent unanticipated health shocks and therefore should not affect the travel decisions of visitors. Thus, being a visitor or a mover should be plausibly exogenous to the local-area health-care spending and treatment intensity.

Our analysis contributes to the literature in several ways. First, we distinguish between in-hospital and post-discharge mortality. Mortality is still high following the discharge from hospital. Therefore, focusing only on in-hospital mortality will not reveal the full picture in answering the question whether more intense treatments provide substantial health benefits. Second, the analysis takes into account potential selectivity in both types of health-care expenditures. For in-hospital health care we compare locals with visitors. For post-discharge health care we compare stayers and movers. If the relationship between expenses and mortality are similar for both pairs of patients selectivity is no issue. Third, in addition to an exploratory analysis using linear probability models for mortality after a specific time interval, we use more sophisticated models that take into account the variation of the mortality rates over the time elapsed since the heart attack. Furthermore, our econometric strategy allows for both observed and unobserved individual patient characteristics affecting in-hospital mortality as well as influencing discharge from hospital and post-discharge mortality.[3]

[3]The traditional approach of modeling mortality rates assumes that post-discharge mortality is independent of in-hospital stay. In reality, however, hospital length of stay might be correlated with both in-hospital mortality, hospital discharge and transfer from hospital, while realization

The remainder of the paper is organized as follows: the next section presents a brief overview of previous economic studies on the relationship between health-care expenditures and mortality related to heart attacks. These studies are from different countries and time periods using a variety of identification strategies to take into account local supply factors, i.e., health-care expenditures being determined by demographic circumstances. Some studies use the distance to hospital, other studies compare local patients with visitors, study recently migrated patients or exploit reforms affecting patients' choice of hospitals. The studies differ in terms of conclusions with respect to the relationship between health-care expenditures and mortality. The third section presents our dataset providing descriptive statistics about our main variables in the analysis. We show that there is substantial cross-regional variation both in in-hospital and post-discharge health-care expenditures. Across regions both types of expenditures are positively correlated. We also provide information about the four types of patients we pairwise distinguish in our analysis, i.e. locals – visitors and stayers – movers. We show that the cross-regional differences in health-care spending are not correlated with cross-regional difference in age or comorbidities. The fourth section presents an exploratory analysis using linear probability models for in-hospital and post-discharge mortality of patients who suffered from a heart attack. The results suggest that mortality of both locals and visitors are affected by personal characteristics and residence characteristics. In-hospital health-care expenditures have a significant negative effect on the probability to die in-hospital. Post-discharge health-care expenditures reduce mortality after the discharge from hospital.

The fifth section discusses the way our analysis uses duration information. We model multiple durations: duration of in-hospital stay, distinguishing between discharge from hospital, transfer from hospital and mortality in hospital. And, we investigate the post-discharge duration until mortality. Using a multivariate mixed proportional hazard (MMPH) framework we allow residence characteristics as well as observed and unobserved personal characteristics to influence the four types of durations. By allowing for correlation between the unobserved characteristics, the models take into account potential unobserved selectivity in hospital dismissals. By

of each duration may have an effect on long-term mortality after discharge.

and large the duration analysis confirms the conclusions from the linear probability analysis that higher health-care expenditures reduce mortality. The sixth section explores the mechanisms through which higher health-care expenditures reduce mortality. Finally, the seventh section summarizes our main findings that mortality depends on age of the patient, the way the heart attack was treated in hospital, residence characteristics, comorbidities and the elapsed time period since the heart attack occurred. Our main conclusion is that the substantial regional variation in mortality is very much related to regional variation in health-care expenses.

2 Previous studies

Our paper is at the intersection of the effectiveness of medical treatment of heart attacks (AMI) and the consequences of regional variation in health-care expenditures. In this section we provide a brief overview of recent studies on both topics.

2.1 Medical treatment of heart attack

When studying the effectiveness of medical treatment of a heart attack one has to consider possible endogeneity of the treatment, i.e., depending on the seriousness of the heart attack a particular treatment will be used. If some treatments are only used with a severe heart attack one might erroneously conclude that this treatment is not effective while conditional of the severity of the heart attack one might draw a different conclusion. Furthermore, one has to consider the possibility that there are unobserved characteristics of patients that affect both treatment and outcome. Patients with poor health may receive a different treatment than patient in good health. If the treatment is correlated with a higher mortality one might erroneously conclude that this is due to the treatment while in fact it may be related to the poor health status of the patient. To account for endogeneity and unobserved patient characteristics often an instrumental variable approach is used. A popular instrumental variable is the distance to particular hospitals because this distance is likely to determine the nature of the treatment while not directly influencing the health outcome of the treatment. Heart attacks are frequently studied because the severity of the health shock will force the use of the nearest hospital.[4] This rules out the possibility that a particular hospital is chosen for example because of its reputation. To account for spurious cross-regional correlation between health-care spending and health outcomes information about visitors suffering from a heart attack may be used. Because of the urgency of the treatment visitors will not be transferred to their region of residence. Studying heart attack patients visiting a different region will therefore correct for the potential correlation between regional health status of the population and regional health-care expenditures.

There are quite a few studies that use an instrumental variable approach. McClellan et al. (1994) for example analyze four-year survival rates of U.S. patients after a heart attack using the distance of patients to particular hospitals as instrumental variables to account for unobserved characteristics and endogeneity of treatment types. They conclude that admissions of patients into hospitals treating more AMI patients translates into a decrease of mortality by less than one percent, after taking into account access to possible treatments. The authors also note that treatments administered within the first 24 hours after admission provide the best long-term survival benefits. Frances et al. (2000) study whether mortality after a heart attack is influenced by whether or not a cardiologist is involved in the treatment. To account for selectivity in the assignment of a patient to a cardiologist an instrumental variable approach is used based on the difference in distance from a patient's home to the nearest cardiologist hospital and the nearest non-cardiologist hospital. Their main conclusion is that treatment by a cardiologist does not have a significant effect on mortality of heart attack patients. Cutler (2007) analyzes U.S. data to study the benefits of revascularization procedures up to 17 years after a heart attack. To account for selectivity the instrumental variable used is the differential distance to a hospital capable of providing revascularization. The main conclusion is that revascularization is highly effective in reducing mortality after a heart attack. Sanwald and Schober (2017) analyze survival rates of heart attack patients in Austria. They focus on the effects of patients being initially admitted to hospitals providing percutaneous coronary interventions (PCI). To select for selectivity they use as instrumental variable the distance between the patient

[4] Heart attacks are also frequently studied because the health outcome – mortality – is easily measured and often occurs in hospital.

residence and the nearest hospital providing PCI concluding that the use of PCI substantially reduces mortality following a heart attack.

Doyle (2011) analyzes the relationship between health-care spending and health outcomes focusing on heart-related emergencies using a different identification strategy. Some areas spend more on health care because they have greater levels of intensive care services and higher staff-to-patient ratios. Doyle studies hospital discharges in the state of Florida finding that areas with a higher treatment intensity of patients with heart-related emergencies achieve better results in terms of reduced in-hospital mortality. To account for possible endogeneity, the analysis exploits information about visitors, i.e. patients experiencing a health attack when visiting Florida.

Moscelli et al. (2018) use a policy change for identification. They study the effects of a relaxation of constraints on the choice of hospital in the English National Health Service investigating whether this affected mortality for three high volume emergency conditions with high mortality risks: heart attack, hip fracture and stroke. The idea of the reform was that greater choice would increase competition between hospitals and thus improve the quality of care. The authors find reduced mortality related to hip fractures, but no effects for heart attacks and strokes.

Chandra and Staiger (2020) analyze a US dataset on patient survival following heart attack focusing on potential allocative inefficiencies in treatment decisions across hospitals. They find that variation in the choice of reperfusion treatment is partly related to differences in comparative advantages of hospitals in terms of the effectiveness of the treatment. They find evidence of allocative inefficiencies but this seems to be related to hospital having imperfect information and a misperception of their comparative advantage rather than to medical malpractice.

2.2 Regional variations in health-care expenditures

Cross-regional variation in health-care expenditures is a common phenomenon. From an economic point of view it is interesting to find out whether this variation is driven by supply or demand. Demand-driven variation is related to patient health and could be efficient. Supply-driven variation can be related to physician's preferences and may signal inefficiency. As stated earlier, regional variation in treatments for the same health issue may not necessarily reflect inefficiencies as some regions may have hospital-related comparative advantages in terms of the success of certain treatments.

In his overview of causes and consequences of regional variations in health care, Skinner (2011) argues that to understand regional variations, differences in health care, health-care expenditures, health-care prices, health status of the population and income have to be taken into account.[5] Regional variations may also be related to the interplay between and among supply and demand in health-care markets in which there are complex networks of primary care physicians and specialists. According to Sheiner (2014) cross-state spending in the U.S. is mostly associated with health and health behavior with variation in patient characteristics being more important than variation in provider characteristics. She concludes that variation in the differences in health-practice styles is of little importance.

Göpffarth et al. (2016) study the regional variations in health-care expenditure in Germany, a country with a homogeneous health-care system, low co-payments and uniform prices. They find that demography and state of health explain more than half of the regional variation in health-care expenditures while there is no evidence of inefficiencies.

Finkelstein et al. (2016) exploit patient migration to separate variation in the use of health services due to demand factors (patient characteristics such as health or preferences) and supply factors (place-specific variables such as doctors' incentives and beliefs, endowments of physical or human capital and hospital market structure). The analysis is based on an event-study analysis of changes in health-care utilization around moves. The main conclusion is that 40-50% of geographic variation is due to fixed characteristics of patients that they carry with them when they move. The remaining 50-60% is due to place-specific factors. Godøy and Huitfeldt (2020) use Norwegian data to study to what extent regional variation in health-care utilization is driven by place-specific factors as opposed to variation in underlying patient health. To identify hospital region effects the authors follow

[5]He argues that there are two reasons why regional variations in health care are viewed differently from variations in the consumption of products like for example meat and poultry. First, the variations are financed largely by third parties and not by patients receiving treatment. Second, the regional variations in health-care utilization are symptomatic of an enormous lack of knowledge about what works and what does not work in health care.

Finkelstein et al. (2016) exploiting migration of patients across hospital referral regions. The main finding is that the association between health-care spending and overall mortality is absent. For cancer but not for heart problems and external problems there is a negative association.

Also in recent studies on regional variation in health-care expenditures there is no common conclusion about the importance of supply or demand factors. Two examples of the opposing conclusions are Cutler et al. (2019) and Salm and Wübker (2020). Cutler et al. (2019) study whether regional variation in health-care expenditures in the U.S. is caused by patient demand-side factors or physician supply-side factors. Their approach is based on the use of vignettes in patient and physician surveys. The main conclusion is that patient demand is relatively unimportant in explaining regional variation in health-care expenditures. Instead, the most important determinant is physician beliefs about treatment. Salm and Wübker (2020) also analyze regional variation in health-care expenditures in Germany using patient migration to distinguish between demand for and supply of care utilization. They come to the opposite conclusion that patient characteristics determine to a large extent the regional variation in health-care expenditures.

3 Data and descriptives

3.1 Characteristics of the dataset

Slovakia is a European country with about 5.5 million inhabitants of whom about half a million live in the capital Bratislava. Health-care expenditures in 2020 amounted to $2,360 per capita, or around 7.7% GDP, which is slightly below the average OECD health-care spending of 9.9%. The 30-day mortality following admission to hospital with AMI is 13.5%, which is substantially higher than the OECD average of 8.8% (OECD (2021)). Public health care in Slovakia is organized by hospital service area (HSA). HSAs in Slovakia are formally determined by government decree and include one or more neighboring districts, depending on the availability of acute care hospitals in the particular area. Figure 1 plots average health-care utilization by hospital service areas in 2020.[6]

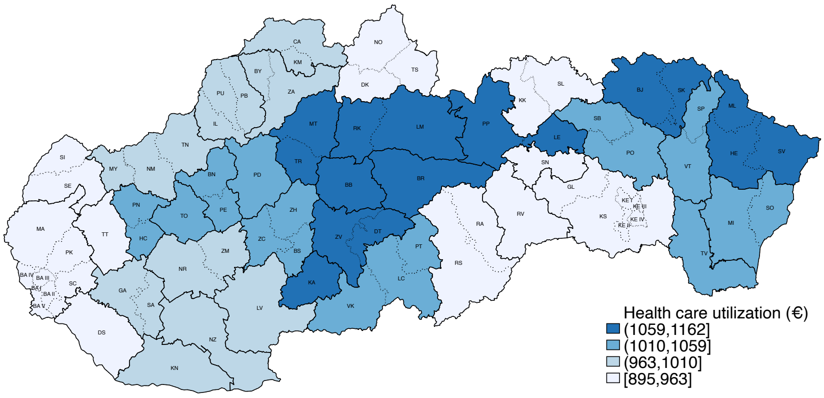


FIGURE 1: HEALTH-CARE UTILIZATION IN SLOVAKIA BY HOSPITAL SERVICE AREA; 2020 (EURO PER PATIENT)

Notes: Solid border lines represent HSAs, dotted lines show district borders.

An average HSA spends around 1017€ per patient on health care. There is a lot of regional variation. The majority of large cities, including Bratislava (BA) in the western part and the second largest city of Košice (KE) in the eastern part of the country have an average utilization in the lowest quartile of the spending distribution. Both regions are the richest in terms of economic performance and have a dense network of specialist outpatient care and large university hospitals. The highest health-care utilization is present mostly in less populated rural areas across the country. This suggests that regional differences are likely related to the underlying health status of the local population.

Health care in Slovakia is based on universal coverage, with the basic insurance package covering nearly all treatments, both inpatient, primary and secondary care as well as prescription medications. There are no co-payments for use of inpatient, primary or secondary care. Out-of-pocket payments mostly include procedures such as IVF, induced abortion, plastic surgery or above-standard accommodation.[7]

[6]Health-care utilization is defined as a sum of all costs, including inpatient and outpatient care, pharmaceutical prescriptions, emergency care etc. accrued by patients during a calendar year, based on their resident HSA. Appendix C provides an overview of all two-letter districts and their full names.

[7]For more information about the Slovak health-care system, see for example Bucek Psenkova et al. (2017).

In our analysis, we use administrative data from the National Health Information Center of Slovakia (NHIC). NHIC administers several national health registries, including a claim database on all health expenditure reimbursements. The dataset combines patient-level data on all procedures provided by public health-care insurance. The databases are linkable through a unique patient identifier obtained at birth. Public health-care insurance is mandatory for every individual who has permanent residency in the Slovak Republic. Therefore the registries effectively cover the whole population.

Our sample includes all patients admitted to hospitals in the calendar years 2014 to 2019 with primary diagnosis code I21 and subcodes corresponding to AMI in the International Statistical Classification of Diseases (ICD) version 10. For each patient, the date of admission, discharge, length of stay, procedures, hospital charges, hospital performing the procedure and individual characteristics such as age, gender and residence are included. Residence characteristics including average educational attainment are based on data from the latest population census, while information about median income is based on 2020 data from the Social Security register. Patients in the dataset are observed until 31st December 2019, all observations beyond this date are considered as right-censored.[8]

Information on comorbidities is extracted from other registries including primary care procedures and pharmaceutical prescriptions. Following Bannay et al. (2016) this information is used to construct the Charlson comorbidity index, according to an algorithm for administrative data developed by Quan et al. (2005). Because of the low occurrence of certain comorbidities such as AIDS or severe liver disease the original 17 categories of the index are collapsed into eight smaller categories. Our dataset is also informative about a variety of post-discharge treatments and procedures, such as the use of cardiac rehabilitation. This allows us to investigate possible mechanisms through which increased spending affects mortality.

In the analysis, we use two types of health-care spending as explanatory vari-

[8]Despite the fact the databases allow us to track patients up to the end of year 2021, we decided to limit the observation window up to the end of year 2019 due to disruptions in delivery of health care during the COVID-19 pandemic. In the sensitivity analysis section we also consider a longer observation window in the analysis of post-discharge survival.

ables:

1. In-hospital end-of-life spending. End-of-life (EOL) spending is calculated as follows: First, an average of total charges for each patient dying in a particular hospital is calculated, similarly to Doyle (2011). Hospital averages are then summarized at the level of the HSA. More formally, EOL spending or as it is sometimes referred to, treatment intensity T in HSA g is equal to:

$$T_g = \frac{1}{H}\sum_{h=1}^{H}\frac{1}{N}\sum_{i=1}^{N} c_{ihg} \tag{1}$$

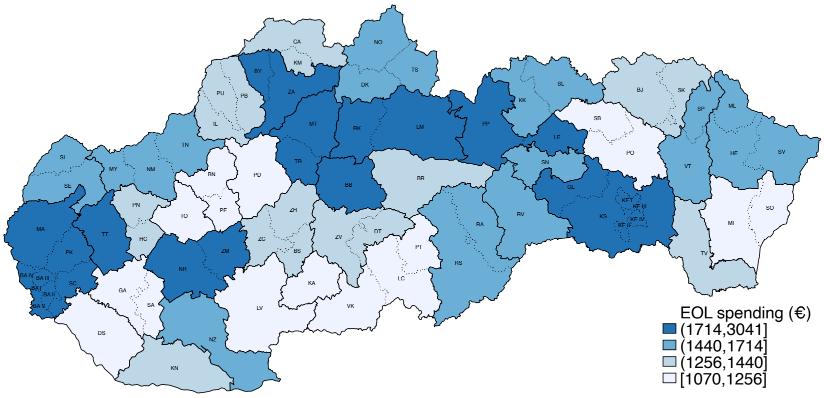
   where c denotes total hospital charges for patient $i(1,...,N)$ dying at the hospital $h(1,...,H)$ in HSA g.

2. Post-discharge spending T_g^P, i.e., expenses on patients surviving heart attacks is defined as the average of total costs billed in primary care and for pharmaceutical treatments related to the ICD-10 diagnoses corresponding to AMI, for patients residing in a region g within the first 6 months after discharge from the hospital:

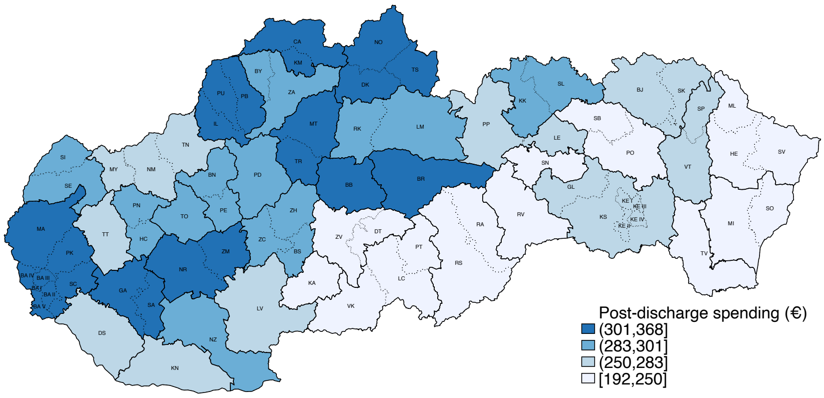
$$T_g^P = \frac{1}{N}\sum_{i=1}^{N} c_{ig}^P \tag{2}$$

   where c_i^P denotes the costs for treatments within the first six months following discharge in HSA g.

The in-hospital EOL spending reflects the quality of the hospital services in terms of the quality of the equipment, staff etc. The post-discharge spending reflects the quality of outpatient services. Figures 2A and 2B provide an overview of HSAs and districts in Slovakia with their average treatment intensity. Not surprising, the highest spending areas are concentrated mostly around larger metropolitan areas, while lower spending areas are mostly rural.



A: End-of-Life Spending



B: Post-discharge Spending

Figure 2: End-of-Life and Post-discharge Spending in Slovakia by Hospital Service Area; 2020 (Euro per patient)

Notes: Solid border lines represent HSA, dotted lines show district borders.

Although the nature of health-care expenditures is very different for EOL spending and post-discharge health-care spending as shown in figure 3, both types of expenditures are positively correlated.

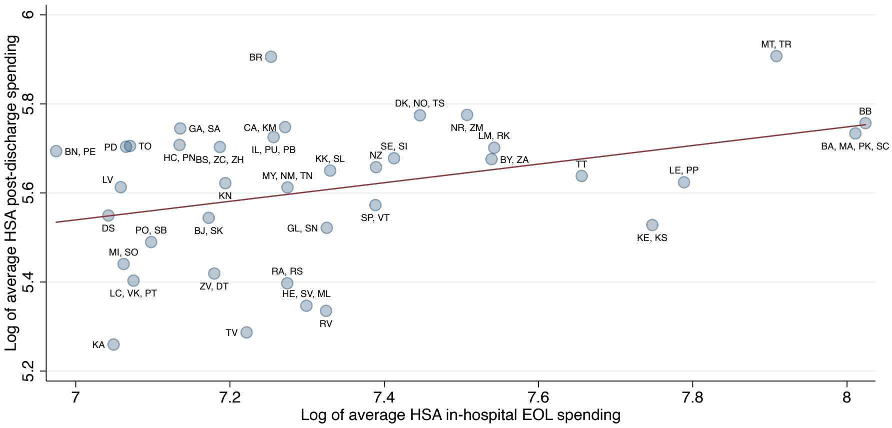


Figure 3: Average HSA End-of-Life Spending vs. Average HSA Post-discharge Health-Care Spending

Notes: Dots represent HSA, solid line represents fit from a linear regression.

3.2 Visitors and movers

Information about the relationship between health-care spending and mortality of visitors and movers can be helpful in the identification of the effects of health-care spending on mortality.

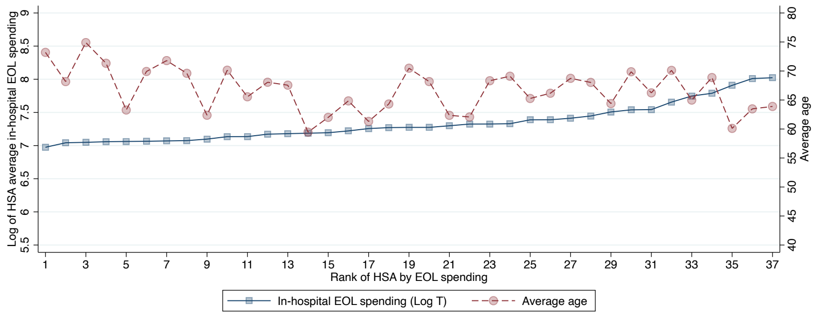
Regional health-care expenditures may be high because of the poor health of its inhabitants. If so, this will bias the estimated effect of expenditures on health outcomes. To investigate the relevance of this, we also analyze mortality of visitors with a heart attack. A visitor is defined as a patient hospitalized with an AMI outside of their HSA, provided there is a cardiac center capable of performing PCI in patient's home HSA.[9] For patients with ST-elevated AMI and with no PCI center in their home HSA, we expand the catchment area to 90 minutes of travel time from their home municipality. In other words, we do not consider patients as visitors if they were hospitalised in a PCI center within 90 minutes of travel time from home, provided that there is no PCI center in their resident HSA. While

[9]PCI are minimally invasive procedures used to open clogged coronary arteries – those that deliver blood to the heart. Standard treatment guidelines for heart attacks recommend a transport of patients into a PCI center within 90 minutes since confirmed diagnosis of ST-elevation AMI. This is also the case in Slovakia, by recommendation of the official guidelines published by the Ministry of Health.

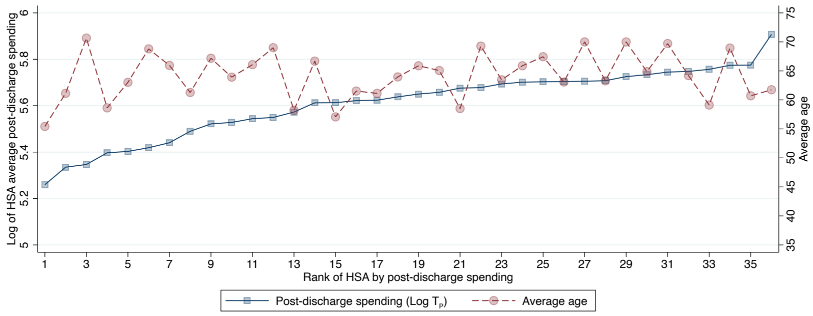
visitors are helpful in the analysis of in-hospital spending on mortality, they are not informative about long-term mortality related to their home HSA once recovering from AMI. To establish a causal relationship between post-discharge spending and long-term mortality, we use information about patients migrating between regions before they experienced heart attack.

The use of visitors and movers as an identification strategy is particularly appealing in the analysis of regional variations in spending and mortality, since whether a patient is a visitor or a mover is unrelated to local spending at the HSA level, provided there is no systematic sorting to certain areas. A conceivable scenario which would invalidate causal inference of health-care spending levels on mortality is that areas spending more on health care attract wealthier visitors, who may be in better health overall. Similarly, certain areas with lower spending, concentrated mostly in rural areas may attract certain age cohorts.

Figure 4 plots the average age of visitors and movers across the HSA spending distribution. For visitors, there is a noticeable decrease in age within the top 3 spending HSAs. For movers, there is no visible relationship. We also formally test the difference between the bottom quartile and the remaining quartiles. For visitors, the age decline is statistically significant when comparing the bottom and the top quartiles, while for movers there are no differences. To address these differences, all empirical analyses control for age of the patient, while in a sensitivity analysis we show the effects of health-care spending on mortality in separate age samples.



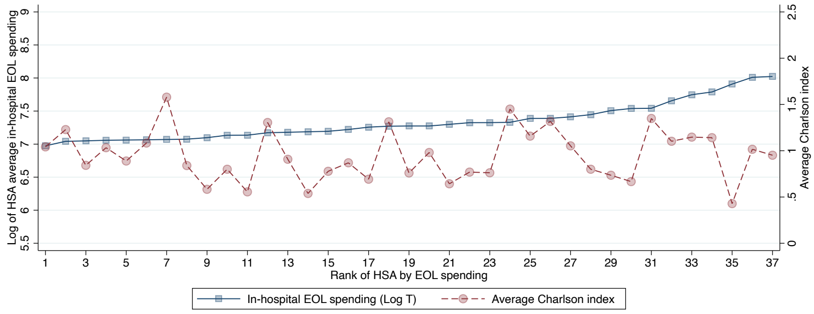
A: Visitors



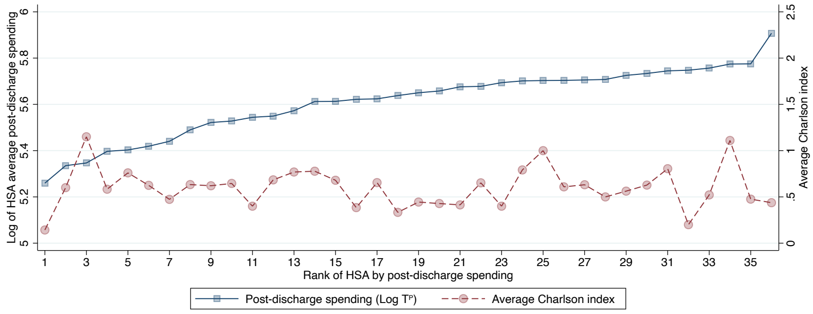
B: Movers

Figure 4: Age vs. HSA Spending Rank

To test whether certain HSAs attract patients with different health status, a similar check is provided for Charlson comorbidity index in the respective HSA, displayed in figure 5. For both groups, there are no visible trends across the spending distribution. We also test for the differences in the share of patients with specific comorbidities across quartiles, again finding no significant differences except for a slightly higher incidence of cardiovascular disease for visitors in the 3rd quartile and a slightly lower incidence of respiratory disease for movers when compared to the lowest quartile. The results are summarized in tables A6 and A7.



A: Visitors



B: Movers

Figure 5: Charlson Index vs. HSA Spending Rank

Patients migrating between regions are only useful for identification of causal effects on post-discharge spending if the moves occur in both directions, i.e. patients move both from low-spending regions to high-spending regions and vice versa. To investigate whether this is the case, we follow Finkelstein et al. (2016) and Godøy and Huitfeldt (2020) and plot the distribution of difference in post-discharge spending between the origin and destination HSAs. As shown in figure 6 this distribution is fairly symmetrical.

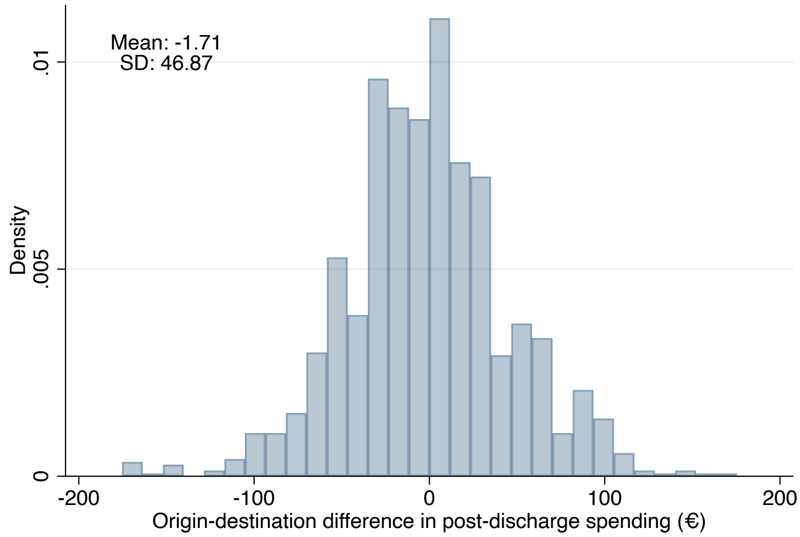


Figure 6: Origin-Destination Difference in HSA Post-discharge Spending

3.3 Descriptive statistics

Table 1 provides summary statistics of the dataset, distinguished by quartiles of the distribution of health-care expenditures.[10] Panel A shows the average (log) in-hospital costs over the four quartiles and selected sample characteristics for locals and visitors, while panel B provides similar information about post-hospital discharge health-care spending for the samples of stayers and movers.

Table 1 shows the distribution of two outcome variables, i.e. in-hospital mortality and post-discharge mortality. As shown in panel A, for both locals and visitors, in-hospital mortality is highest for the quartile with the lowest in-hospital expenditures. With respect to overall mortality also here for locals the lowest quartile of the in-hospital expenditures has the highest mortality. A similar relationship is present for visitors, where the lowest-spending quartile of HSAs has the highest in-hospital mortality. The same relationship holds for post-discharge

[10] Visitors may be relocated from a hospital in the region they visited to a hospital in the region of residence. For visitors, we use the health-care expenditures of the first hospital they entered after their heart attack.

mortality. Part of the inverse relationship between in-hospital EOL spending and mortality may be due to differences in patient characteristics. For example, panel A shows that in the quartile with the highest in-hospital expenditures average age is lowest, both for locals and visitors. Furthermore, in this quartile among locals the value of the Charlson index is lowest. This also holds for visitors but here the differences are not statistically significant different from each other.

Table 1: Selected Descriptive Statistics by Quartiles of Health-Care Spending

	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Panel A. In-hospital mortality								
	Locals				Visitors			
Health care spending								
In-hospital EOL ($\log T_g$)	7.144	7.467*	7.809*	8.017*	7.176	7.444*	7.744*	8.019*
Sample characteristics								
In-hospital mortality	0.072	0.042	0.025*	0.043*	0.091	0.046*	0.036*	0.042*
Post-discharge mortality	0.308	0.247	0.233*	0.228*	0.300	0.269	0.267	0.237*
Age	69.0	67.5	66.5*	66.2*	67.6	66.2	65.8	63.7*
Charlson index	0.998	0.879	0.959	0.811*	0.980	0.873	1.091	0.978
Observations	10,840	10,227	9,879	10,181	919	655	861	1,086
Panel B. Post-discharge mortality								
	Stayers				Movers			
Health care spending								
Post-discharge ($\log T_g^P$)	5.434	5.624*	5.716*	5.790*	5.446	5.623*	5.719*	5.789*
Sample characteristics								
In-hospital mortality	0.043	0.054	0.054	0.034	0.023	0.022	0.017	0.027
Post-discharge mortality	0.254	0.274	0.258	0.236	0.203	0.196	0.182	0.203
Age	66.8	67.6	67.8*	66.8	64.1	62.9	65.6	64.0
Charlson index	0.936	0.960	0.888	0.894	0.816	0.692	0.799	0.872
Observations	12,390	11,819	12,014	7,287	256	321	413	148

Notes: * Significantly different from bottom quartile at the 5-percent level. Standard errors clustered at the HSA level.

Panel B of Table 1 provides similar descriptive statistics when the samples of stayers and movers are split-up by quartile of post-discharge health-care expenditures. Now, there is no clear relationship between health-care expenditures and mortality. There are also hardly any differences by quartile of post-discharge health-care expenditures and average age or Charlson index.

4 Exploratory analysis

By way of exploratory analysis we replicate Doyle (2011), who uses linear probability models (LPM) explaining in-hospital mortality for patients and visitors estimating the parameters of the following equation:

$$M_i = \alpha + \log(T_{gi})\zeta + x_i'\beta + w_{ci}'\gamma + \epsilon_i \tag{3}$$

where M_i represent a binary indicator denoting whether patient i died in hospital, T_{gi} is the in-hospital EOL spending in HSA region g, x is a vector of observed characteristics of the patient and treatment characteristics, w denotes vector of characteristics of residence c in which the patient was hospitalized, and ϵ_i represents an error term.

Observed characteristics are gender, age, comorbidities of the patient, whether the heart attack happened during a weekend and the quarter of the year.[11] Residence characteristics are median income, share of inhabitants with university education, and whether or not the residence is in a rural area.

Panel A of Table 2 presents the parameter estimates related to in-hospital health-care costs. Columns (1) and (2) report estimates for locals (without and with residence characteristics), while columns (3) and (4) report estimates for visitors (without and with residence characteristics). All parameter estimates are significantly negative – the higher the in-hospital costs the lower in-hospital mortality. Contrary to Doyle, we also find a significant negative effect of local-area treatment intensity for local patients and not just for visitors. Interestingly, the magnitude of the parameter estimates is similar for locals and visitors. This suggests that selectivity in regional treatment is not an issue.

In panel B, estimates of a LPM model for post-discharge mortality are presented, where M_i now denotes a binary variable equal to 1 if patient died after

[11] The quarter of year is included, since there is a well-documented seasonality of cardiovascular diseases, with greater incidence and mortality observed during winter months. Furthermore, concurrent influenza and increase in air pollution during winter are likely contributors to worse health outcomes (Stewart et al. (2017)).

discharge from hospital within 2 years, restricting the sample to patients for whom we have information for at least 2 years since discharge. For stayers the effect of post-discharge health-care spending is negative and statistically significant. For movers the coefficients are also negative, but imprecisely estimated. This also implies that the parameter estimates of stayers and movers are not significantly different from each other. This again confirms that regional selectivity is not an issue.

Appendix A.1 table A1 shows the full set of parameter estimates related to those presented in Table 2. From these it appears that many of the mortality effects are similar in-hospital and post-discharge. Mortality increases with age, while post-discharge mortality of males is higher and about the same as for females in hospital. Mortality increases with the length of hospital stay but this is most likely reverse causality, i.e., those who stay longer in hospital are more likely to die. Those with median income in the highest quartile have a higher post-discharge mortality, similarly to those living in rural areas. Nearly all comorbid conditions significantly increase mortality after discharge from hospital.

Table 2: Health Outcomes for Heart Attacks – Linear Probability Models

Dependent variable: mortality rate	(1)	(2)	(3)	(4)
Panel A. In-hospital mortality				
	Locals		Visitors	
In-hospital EOL spending ($\log T_g$)	−0.035	−0.043	−0.045	−0.047
	(2.2)**	(3.7)***	(2.2)**	(2.4)**
Mean of dependent variable	0.046		0.054	
Observations	41,127		3,521	
Panel B. 2-year post-discharge mortality				
	Stayers		Movers	
Post-discharge spending ($\log T_g^P$)	−0.053	−0.059	−0.032	−0.124
	(2.2)**	(2.5)**	(0.4)	(1.2)
Mean of dependent variable	0.195		0.135	
Observations	25,361		652	
Residence characteristics	No	Yes	No	Yes

Notes: All estimates include personal characteristics. Robust absolute t statistics clustered at the HSA level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

5 Duration models

Linear probability models may be informative about the relationship between health-care spending and mortality. However, there are various transitions involved: mortality in hospital, dismissal from hospital, transfers to other hospitals and post-hospital mortality. All these transitions may be related through observed and unobserved characteristics. Therefore, we extend our analysis by using duration models in which all these relationships can be taken into account.

5.1 Mortality rates

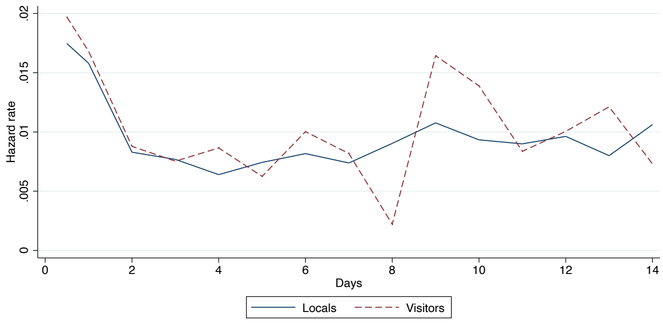
Figure 7 presents empirical hazard rates of in-hospital mortality and mortality after discharge for both visitors and locals. Figure 7A plots daily in-hospital mortality rates for the first 14 days after being admitted to hospital with AMI. The hazard rate peaks the first few days after admission, and then rises again over the course of the observation window, suggesting that more severe cases are kept longer in hospital. Figure 7B displays mortality rates after discharge from hospital. The mortality rate peaks shortly after discharge. This could suggest that patients may have been discharged from hospital too early. However, this phenomenon is not unique to Slovakia. For example, Karlson et al. (1991) find a similar peak in the post-discharge mortality rate for Swedish AMI patients. Figure 7C plots weekly mortality rates within one year since admission to hospital. The highest mortality rate is clearly within the first weeks after admission to decrease thereafter staying nearly constant later on.

5.2 Model specification

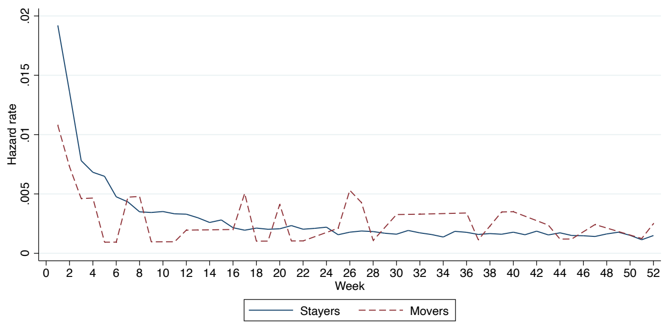
To estimate the effects of treatment intensity on patient survival, we use a multivariate mixed proportional hazard rate framework, where both observed and unobserved characteristics are allowed to affect the various transition rates.[12] Since in-hospital mortality and discharge from hospital are likely to be correlated with hospital length of stay, we model both outcomes as competing risks. Furthermore,

[12]See Picone et al. (2003) for an example of a competing risk model used to analyze hospital length of stay and the discharge destination such as home care or skilled nursing.

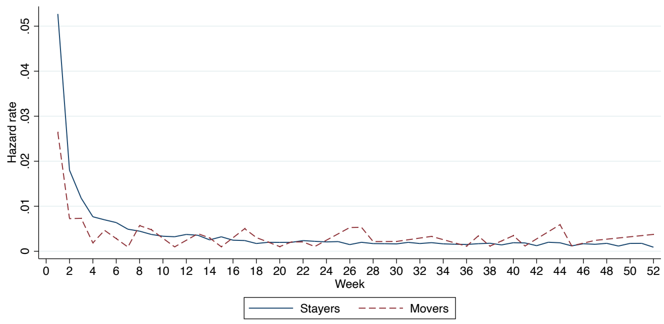
the realization of both durations might have an effect on post-discharge survival through both observed and unobserved factors. To take this potential dependence into account, we estimate all three processes using a discrete mixture of unobserved heterogeneity following Heckman and Singer (1984), where all unobserved components are allowed to be correlated with each other.



A: Daily In-Hospital Mortality Rates



B: Weekly Post-discharge Mortality Rates



C: Overall Weekly Mortality Rates Since Admission

Figure 7: Empirical Mortality Rates

We model the in-hospital mortality rate h, discharge rate s and transfer rate r at duration since heart attack t (omitting the subscript for individuals) conditional on a vector of observed characteristics x, residence characteristics w, the local-area treatment intensity T_g and unobserved characteristics υ as:

$$\theta_j(t \mid x, w, T_g, \upsilon_j) = \lambda_j(t) \exp(x'\beta_j + w'\gamma_j + \log(T_g)\zeta_j + \upsilon_j) \quad \text{for} \quad j = h, s, r \quad (4)$$

where T_g is the local-area spending corresponding to the first hospital's HSA in which a particular patient was hospitalised[13], x and w are defined as previously and υ represents a random effect capturing unobserved heterogeneity. Furthermore, $\lambda_j(t)$ represents individual duration dependence, which is flexibly modeled using a step function:

$$\lambda_j(t) = \exp\left(\sum_k \lambda_{j,k} I_k(t)\right) \quad (5)$$

where $k(= 1, ..., K)$ is a subscript for day-intervals and $I_k(t_l)$ are time-varying dummy variables for subsequent day-intervals when the event (death) occurs. The intervals are defined for days 0-2, 3-4, 5-6, 7-10, 11-15 and more than 15 days. The conditional density function of durations until in-hospital death, hospital discharge or transfer to a different hospital is defined as:

$$\begin{aligned} f(t \mid x, w, T_g, \upsilon_h, \upsilon_s, \upsilon_r) = & \sum_j \theta_j(t \mid x, w, T_g, \upsilon_j) \\ & \exp\left(-\int_0^t \sum_j \theta_j(u \mid x, w, T_g, \upsilon_j)\, du\right) \quad \text{for} \quad j = h, s, r \end{aligned} \quad (6)$$

Note that t is equivalent to the hospital length of stay. The above formula represents the density function of the competing risk part of the model.

The post-discharge mortality rate at duration since hospital discharge t_d conditional on observed characteristics x, residence characteristics w, post-discharge

[13] We include the first-hospital treatment intensity since the crucial treatment decisions determining survival of patients such as whether to administer reperfusion therapy or PCI are time-dependent and are unlikely to be performed after more than 24-48 hours since the diagnosis (O'Gara et al. (2013)).

treatment intensity T_g^P and unobserved characteristics ν is modeled similarly:

$$\theta_d(t_d \mid x, w, T_g^P, \nu) = \lambda_d(t_d) \exp(x'\beta_d + w'\gamma_d + \log(T_g^P)\zeta_d + \nu) \tag{7}$$

Stepwise duration dependence λ_d is defined as in equation 5 with intervals for days 0-2, 3-4, 5-8, 9-16, 17-30, 31-60, 61-180 and more than 180 days. The conditional density function of completed durations until death post-discharge can be written as:

$$\begin{aligned} f_d(t_d \mid x, w, T_g^P, \nu) = {} & \theta_d(t_d \mid x, w, T_g^P, \nu) \\ & \exp\left(-\int_0^{t_d} \theta_d(s \mid x, w, T_g^P, \nu)\, ds\right) \end{aligned} \tag{8}$$

The potential correlation between the unobserved components in the hazard rates for in-hospital mortality, hospital discharge, hospital transfer and post-discharge mortality is taken into account by specifying the joint density function for the duration of time until in-hospital death, transfer or discharge t and the duration of time until death after discharge t_d, conditional on x, w T_g and T_g^P. We assume that the random effects υ_h, υ_s, υ_r and ν are specified following a discrete mixing distribution G, where each of the components has two points of support:

$$\begin{aligned} g(t, t_d \mid x, w, T_g, T_g^P) = {} & \int_{\upsilon_h}\int_{\upsilon_s}\int_{\upsilon_r}\int_{\nu} f(t \mid x, w, T_g, \upsilon_h, \upsilon_s, \upsilon_r) \\ & f_d(t_d \mid x, w, T_g^P, \nu)\, dG(\upsilon_h, \upsilon_s, \upsilon_r, \nu) \end{aligned} \tag{9}$$

The full mixing distribution yields 16 possible combinations, each describing types of patients with different hazard rates of in-hospital mortality, hospital discharge, transfer from hospital and post-discharge mortality. The probabilities associated with 16 mass points of the joint distribution are defined as:

$$\begin{aligned}
p_1 &= \Pr(\nu_1, \upsilon_{s,1}, \upsilon_{h,1}, \upsilon_{r,1}), & p_2 &= \Pr(\nu_2, \upsilon_{s,1}, \upsilon_{h,1}, \upsilon_{r,1}) \\
p_3 &= \Pr(\nu_1, \upsilon_{s,2}, \upsilon_{h,1}, \upsilon_{r,1}), & p_4 &= \Pr(\nu_2, \upsilon_{s,2}, \upsilon_{h,1}, \upsilon_{r,1}) \\
p_5 &= \Pr(\nu_1, \upsilon_{s,1}, \upsilon_{h,2}, \upsilon_{r,1}), & p_6 &= \Pr(\nu_2, \upsilon_{s,1}, \upsilon_{h,2}, \upsilon_{r,1}) \\
p_7 &= \Pr(\nu_1, \upsilon_{s,2}, \upsilon_{h,2}, \upsilon_{r,1}), & p_8 &= \Pr(\nu_2, \upsilon_{s,2}, \upsilon_{h,2}, \upsilon_{r,1}) \\
p_{10} &= \Pr(\nu_1, \upsilon_{s,1}, \upsilon_{h,1}, \upsilon_{r,2}), & p_{11} &= \Pr(\nu_2, \upsilon_{s,1}, \upsilon_{h,1}, \upsilon_{r,2}) \\
p_{11} &= \Pr(\nu_1, \upsilon_{s,2}, \upsilon_{h,1}, \upsilon_{r,2}), & p_{12} &= \Pr(\nu_2, \upsilon_{s,2}, \upsilon_{h,1}, \upsilon_{r,2}) \\
p_{13} &= \Pr(\nu_1, \upsilon_{s,1}, \upsilon_{h,2}, \upsilon_{r,2}), & p_{14} &= \Pr(\nu_2, \upsilon_{s,1}, \upsilon_{h,2}, \upsilon_{r,2}) \\
p_{15} &= \Pr(\nu_1, \upsilon_{s,2}, \upsilon_{h,2}, \upsilon_{r,2}), & p_{16} &= \Pr(\nu_2, \upsilon_{s,2}, \upsilon_{h,2}, \upsilon_{r,2})
\end{aligned} \tag{10}$$

where p_n is assumed to follow a multinomial logistic distribution:

$$p_n = \frac{\exp(\alpha_n)}{\sum_n \exp(\alpha_n)}, \; n = 1, ..., 16 \tag{11}$$

with α_{16} normalized to zero and $p_{16} = 1 - p_1 - p_2 - ... - p_{15}$. The parameters of the model are estimated using the method of maximum likelihood.

5.3 Parameter estimates

Table 3 presents the main parameter estimates, i.e. the effects of health-care spending on mortality.[14] Panel A shows estimates for in-hospital mortality based on the samples of locals and visitors, while panel B shows estimates for post-discharge mortality based on the samples of stayers and movers. Columns (1) and (3) present the parameter estimates if unobserved heterogeneity is ignored and the various hazard rates are estimated separately. Columns (2) and (4) shows the parameter estimates when the four hazard rates are jointly estimated taking potential correlation between the four unobserved heterogeneity terms into account.

Panel A shows that in-hospital spending has a significant negative effect on in-hospital mortality of locals. The differences between the parameter estimates

[14]The full set of estimates for columns (1)-(4) are presented in Appendix tables A2 and A3. These Appendix tables also contain the parameter estimates for the hospital discharge and transfer rates.

in the two columns is small. So, taking unobserved heterogeneity into account is not very important. The same holds for the parameter estimates for visitors. The effects of in-hospital EOL spending on in-hospital mortality are also very similar for locals and visitors which suggests that selectivity or effects being contaminated by other differences between HSAs is not very important either.

From panel B it is clear that post-discharge spending has a significant negative effect on post-discharge mortality for both stayers and movers. The magnitude of the effect is larger for movers than it is for stayers although the parameter estimates for movers are somewhat imprecisely estimated.

Table 3: Health Outcomes for Heart Attacks – Duration Models

Mortality rate	(1)	(2)	(3)	(4)
Panel A. In-hospital mortality				
	Locals		Visitors	
In-hospital EOL spending ($\log T_g$)	−0.753	−0.767	−0.675	−0.719
	(5.5)***	(3.7)***	(2.4)**	(1.9)*
Average mortality	0.046		0.054	
Observations	41,127		3,521	
Panel B. Post-discharge mortality				
	Stayers		Movers	
Post-discharge spending ($\log T_g^P$)	−0.289	−0.280	−0.924	−0.971
	(2.0)**	(3.1)**	(1.9)*	(1.9)*
Average mortality	0.219		0.175	
Observations	43,510		1,138	
Unobserved heterogeneity	No	Yes	No	Yes

Notes: All estimates contain personal characteristics and residence characteristics. The full set of estimates for all equations of the main model is presented in Appendix tables A2, A3, A4 and A5. Robust absolute t statistics clustered at the HSA level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

The full set of parameter estimates is presented in Appendix tables A2, A3, A4 and A5. Many of the mortality parameter estimates are similar in effects to those presented in Appendix table A1. Table A3 shows that age has a positive effect on mortality. Older patients stay in hospital longer than younger patients. Males are as likely to die in hospital as females while they are more likely to die after hospital discharge. Many comorbidities increase mortality rates in and out of hospital and they increase hospital stay. In-hospital mortality is highest in the first duration interval and approximately constant after that. Post-discharge mortality rates exhibit negative duration dependence; hospital discharge rates have positive duration dependence. While we model a discrete distribution of unobserved heterogeneity with 16 points of support in practice only a few points of support are identified. Conditional on observed characteristics and duration dependence there are three to five types of patients who differ in unobserved terms from each other. Often the unobserved heterogeneity is highly correlated between in-hospital mortality and post-discharge mortality suggesting that unobserved health status or unobserved severity of the heart attack are important.

5.4 Sensitivity analysis

To investigate the robustness of our main findings we perform a sensitivity analysis on the group of movers and visitors, focusing on potential heterogeneity by gender, age and comorbidities. The results are shown in table 4. Columns (1) and (3) report the parameter estimates of post-discharge spending, while columns (2) and (4) report the estimates for in-hospital EOL costs. The results are based on our baseline estimate presented in column (4) of table 3. Overall, the results are in line with the baseline estimates. All coefficients have negative sign, although not all parameters are precisely estimated. The effect of post-discharge spending on post-discharge mortality seems to be higher for those older than age 65. There is some evidence of gender-specific heterogeneity, since the effect of in-hospital spending is not different from zero for males. Finally, we also investigate whether the results for post-discharge mortality are not driven by observing certain patients for only a short period of time. In order to do so, we extend the observation period of movers sample up to the end of year 2021 and define the outcome variable as 2-year mortality. Durations beyond 730 days are considered as right-censored at the 730th day. This way all patients in the sample are observed for at least 2 years since discharge (our main sample considers all AMI-related hospitalisations up to 31st December 2019). The estimated coefficient of post-discharge mortality is even larger in magnitude and statistically significant at the 5% level (not reported).

Table 4: Health Outcomes for Heart Attacks – Sensitivity Analysis

	Movers	Visitors	Movers	Visitors
	Mortality	In-hospital mortality	Mortality	In-hospital mortality
	(1)	(2)	(3)	(4)
Panel A. By age				
	Age < 65		Age $\geq$ 65	
Spending $\log(T_g^P)$, $\log(T_g)$	−0.854	−0.412	−0.982	−0.694
	(1.7)*	(1.1)	(1.9)*	(1.5)
Observations	1,138	1,641	1,138	1,880
Panel B. By gender				
	Males		Females	
Spending $\log(T_g^P)$, $\log(T_g)$	−0.924	−0.656	−0.921	−0.829
	(1.8)*	(1.3)	(1.8)*	(2.3)**
Observations	1,138	2,250	1,138	1,271
Panel C. By comorbidity status				
	Charlson index = 0		Charlson index $\geq$ 1	
Spending $\log(T_g^P)$, $\log(T_g)$	−0.923	−0.848	−0.936	−0.624
	(1.8)*	(1.8)*	(1.9)*	(1.3)
Observations	1,138	1,710	1,138	1,811

Notes: All estimates include full set of controls and UH. Due to low number of events for certain categorical variables in split samples, estimates for movers are based on a pooled sample with interaction terms for respective groups. Robust absolute t statistics clustered at the HSA level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

5.5 Magnitude of the effects

To indicate the magnitude of various effects, we performed simulations based on parameter estimates for movers and visitors from our baseline specification in table 3. The results are summarized in table 5. The simulations of the effects are based on a reference patient, defined as a male individual with the sample median age of 67 years, hospitalized for the sample mean of five days and having two common comorbidities (diabetes and cardiovascular disease). The predicted mortality is then simulated over the spending distribution. To show how the predicted mortality changes when the spending is fixed, the exercise is repeated across the age distribution. The simulation of the age effects is based on a male individual with the same comorbidities, hospitalised or residing in the median spending HSA. Finally, the simulation of comorbidity effects is again based on a median-aged male, with median HSA-spending. More details about the simulations are provided in Appendix B.1.

TABLE 5: EFFECTS OF SPENDING AND AGE ON MORTALITY

Spending effects			Age effects		
Spending percentile		Predicted mortality	Age percentile		Predicted mortality
Panel A. In-hospital mortality at 5 days					
1%	(1141€)	15.8	99%	(91 years)	27.4
25%	(1339€)	15.0	75%	(76 years)	18.9
50%	(1436€)	16.0	50%	(67 years)	13.9
75%	(2697€)	12.7	25%	(59 years)	10.6
99%	(3041€)	9.0	1%	(37 years)	4.7
Panel B. Post-discharge mortality at 1 year					
1%	(192€)	19.0	99%	(91 years)	50.8
25%	(250€)	15.5	75%	(76 years)	24.0
50%	(282€)	14.0	50%	(67 years)	14.0
75%	(301€)	13.2	59%	(59 years)	8.3
99%	(367€)	11.0	1%	(37 years)	2.0

It is clear that being hospitalized with AMI in the lowest spending HSA coincides with a substantial higher mortality than being hospitalized in a higher-spending HSA. An increase of in-hospital EOL spending from the first to the third quartile of spending distribution reduces mortality for a median male[15] patient by 2.3 percentage points, while an increase of spending from the 1st to 99th percentile is associated with an decrease of mortality of almost seven percentage points. For a comparison, Doyle (2011) reports a difference of 2.8 percentage points in mortality between the first and third quartile of spending distribution. There are also significant differences in mortality by age. A patient aged 59 years hospitalized in a median-spending HSA has a predicted mortality of almost 11%, whereas the same patient aged 76 years has a mortality expectation that is about eight percentage

[15]Predicted survival probabilities for females are similar to those of males.

points higher.

The effects of post-discharge spending on mortality at 1 year since discharge are even more pronounced at the tails of the distribution when compared to the effects of in-hospital spending. The interquartile range of spending is equal to 51€ and is associated with a similar decrease in mortality as with in-hospital spending. As with in-hospital costs, age has substantial effect on mortality if the spending is assumed at the median HSA. A 76 years old patient has a mortality rate that is nearly 16 percentage points higher compared to the same patient aged 59.

6 Mechanisms

The presented finding that higher health-care spending is associated with lower mortality is interesting but not informative about why this is the case, i.e., about possible mechanisms. For the in-hospital spending we do not have detailed information related to procedures but for post-discharge spending we have disaggregate information. This is helpful in analysis whether there is any relationship between higher spending and occurrence of certain health-care procedures.[16] To investigate whether this is the case, we select the top 10 most frequent used procedures performed for patients following discharge from acute care hospitals, conditional on surviving at least 6 months after the AMI. The counts for the procedures at the patient level are then estimated using a zero-inflated Poisson regression, with all explanatory variables as used in the main specifications presented in previous sections. The results are summarized in table 6.

The most frequent post-discharge procedure among AMI patients is a standard physical examination performed by a general practitioner (GP) doctor. GPs in Slovakia issue referrals and serve as gatekeepers for other primary care specialists. The estimated coefficient on treatment intensity for these procedures is positive, suggesting that higher-spending HSAs have a higher incidence of GP encounters for AMI patients. The three following procedures are specific blood tests.

[16]While our dataset includes detailed information about post-discharge procedures, it does not contain detailed information about in-hospital procedures, except whether a bypass surgery or a PCI intervention was performed. See for example Doyle (2011) for a disaggregation of in-hospital procedures of AMI patients and their relationship with health-care spending.

Electrolyte imbalances in AMI patients are not uncommon, while maintenance of adequate serum levels is critical to prevent adverse events such as ventricular arrythmias (Goyal et al. (2012)). Activated partial thromboplastin time (aPTT) and prothrombin time (PT) measure function of blood clotting. Heart attacks are often caused by a formation of blood clots blocking arteries delivering blood to the heart. Due to this, patients after AMI are often prescribed anti-coagulants. Some studies such as Granger et al. (1996) find an association between increased aPTT and risk of reinfarction. Cardiac markers such as troponin and creatine kinase (CK) are indicators of muscle damage, i.e. are often elevated after AMI. However, the estimated coefficients suggest that HSAs with higher spending perform significantly less of the three laboratory investigations. This might be explained by a fact that continuous monitoring of blood levels of troponin and CK is unlikely to be effective, since both markers are elevated only shortly after heart attack.

Electrocardiography (ECG) is a non-invasive procedure capable of detecting subtle changes in electrical activity of the heart, which is often indicative of various cardiac abnormalities. Studies such as Gill et al. (1996) note that ambulatory ECG monitoring of patients after AMI is important to determine the risk of a subsequent coronary event. Our estimates suggest that higher-spending HSAs perform significantly more ECGs than lower spending HSAs. Although not precisely estimated, the use of other non-invasive imaging procedures such as color flow mapping (CFM), pulse-wave (PW) and continuous-wave (CW) Doppler echocardiography (ultrasound imaging of heart) is pointing in the same direction.

Coronary angiography is a medical imaging technique used to visualize blood vessels. However, according to medical guidelines, its routine use in stable patients is discouraged (Patel et al. (2012)). Thus, from a cost-effectiveness perspective, it is perhaps not surprising that higher-spending regions are performing significantly smaller quantity of these procedures. Finally, patients recovering from AMI often benefit from tailored rehabilitation programs, which include lighter forms of exercise. While there seems to be no apparent difference between low- and high-spending regions in use of exercise therapy solely, there seems to be an increased use of a more complex cardiac rehabilitation.[17]

[17] Cardiac rehabilitation is a customized outpatient program of exercise and education. The program is designed to help improve health and stimulate recovery from a heart attack. In

From all this, we conclude that the reduction in post-discharge mortality in higher-spending regions is likely related to better monitoring of patients, as evidenced by an increased use of ECG, as well as more frequent visits to GP. The use of cardiac rehabilitation programs also appears to be important.

Table 6: Coefficients on HSA post-discharge treatment intensity; top 10 Post-discharge Procedures Among AMI Patients

Procedure codes	Procedure	Count	Coefficient	t-statistic
4, 8, 60, 62, 63	Physical examinations	44,938	0.198	(1.1)
3704, 3705, 3706	Electrolytes (Sodium/potassium)	33,188	−0.760	(3.0)**
3842, 3852	Blood clotting (PT/aPTT)	13,259	−0.667	(1.5)
4485, 3696	Cardiac markers (troponin/CK)	12,504	−0.870	(3.0)**
15c, 5702, 5708	Electrocardiography (ECG)	6,729	1.486	(2.3)**
5744	CFM echocardiography	3,310	0.332	(0.3)
5745	PW/CW Doppler echocardiography	3,244	1.010	(0.6)
512, 513, 514	Exercise therapy	2,184	0.120	(0.2)
5110, 5120, 5121, 5122, 5206, 5612b	Coronary angiography	2,173	−1.584	(3.3)**
87a	Cardiac rehabilitation	877	1.835	(1.5)

Notes: All models estimated with full set of controls as in the main specifications using zero-inflated Poisson regression, where zero counts are modelled as logit. Robust absolute t statistics clustered at the HSA level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

7 Conclusions

This paper uses administrative data to investigate the effects of health-care spending on mortality rates of patients who experienced a heart attack. We distinguish between in-hospital mortality which we relate to in-hospital end-of-life spending and post-discharge mortality which we relate to post-discharge health-care spending.

In the analysis of in-hospital mortality we distinguish between two types of patients, i.e., locals and visitors. Locals use hospital services in their region; visitors are hospitalized in regions different from their region of residence. The distinction between the two types of patients helps us to identify the causal effect of health-care costs on mortality. It is possible that regional variations in health-

Slovakia, this often includes spa cardiac rehabilitation.

care expenditures are related to the health status of the population; i.e. regions with many unhealthy people may spend more on health care. Regions with many unhealthy people may also have a higher mortality. This induces selectivity, i.e., a cross-regional positive association between health-care spending and mortality. Therefore, it may be that the negative effect of health-care spending on mortality is underestimated or even reversed. For visitors this contamination of negative causal effects and positive association is not present. This means that for visitors relating their in-hospital mortality after heart attack to in-hospital expenditures gives a clean estimate of the treatment effect. We find for both locals and visitors a negative effect of in-hospital health-care costs on in-hospital mortality. These effects are of the same magnitude which suggests that selectivity is not an issue and there is a negative causal effect of in-hospital health-care expenditures on in-hospital mortality.

For post-discharge expenditures and post-discharge mortality a comparison between locals and visitors is not helpful to get idea about causal effects since also visitors are likely to be treated in their region of residence. A plausibly exogenous group to analyze the relationship between post-discharge mortality and spending are patients who migrate between regions before experiencing a heart attack. For this sample, we also find significantly negative effects of higher spending on mortality.

All in all, we interpret the negative effects of higher health-care spending on mortality as causal effects. Regional variation in mortality is to a large extent related to regional variation in health-care expenses. The regional variation in health-care spending is related to regional variation in wealth and population density. From this, we conclude that from a health perspective it is better to have a heart attack in a wealthy and densely populated region than to have a heart attack in a poor and sparsely populated region.

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Appendix A

A.1 Additional results and tables

Table A1: Parameter Estimates LPM Models

	Locals		Stayers		Visitors		Movers	
	Mortality		In-hospital mortality		Mortality		In-hospital mortality	
	(1)		(2)		(3)		(4)	
Health-care spending								
In-hospital EOL ($\log T_g$)	−0.04	(3.7)***			−0.05	(2.4)**		
Post-discharge ($\log T_g^P$)			−0.06	(2.5)**			−0.12	(1.2)
Personal characteristics								
Age	0.00	(8.3)***	0.01	(30.5)***	0.00	(5.6)***	0.01	(7.1)***
Male	−0.00	(1.0)	0.00	(0.6)	−0.00	(0.2)	−0.03	(1.2)
AMI of inferior wall (I21.1)	−0.01	(3.6)**	−0.03	(3.8)***	−0.00	(0.2)	0.01	(0.2)
AMI of other sites (I21.2)	−0.01	(2.6)**	0.02	(1.3)	−0.01	(0.4)	−0.08	(1.8)*
AMI of unspecified site (I21.3)	0.03	(1.4)	0.04	(2.2)**	0.01	(0.7)	0.03	(0.5)
Non-ST elevation AMI (I21.4)	−0.04	(5.7)***	−0.02	(3.4)**	−0.06	(6.4)***	0.02	(0.5)
AMI, unspecified (I21.9)	0.02	(1.7)	0.01	(1.5)	0.04	(2.8)**	0.03	(0.8)
Length of stay	−0.01	(8.4)***	0.01	(9.3)***	−0.01	(5.5)***	0.00	(1.5)
Residence characteristics								
Median income 950€-1010€	−0.00	(0.5)	−0.00	(0.0)	0.01	(0.9)	0.07	(1.3)
Median income 1010€-1105€	0.00	(0.1)	−0.00	(0.4)	0.04	(2.8)**	0.10	(2.5)**
Median income >1105€	0.01	(0.4)	0.02	(2.3)**	0.05	(3.8)***	0.08	(1.5)
University	0.00	(1.5)	−0.00	(3.0)**	−0.00	(1.1)	0.00	(0.5)
Rural area	0.00	(0.7)	0.00	(0.4)	−0.01	(1.2)	0.07	(1.5)

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Table A1 – Continued From Previous Page

	Locals		Stayers		Visitors		Movers	
	Mortality (1)		In-hospital mortality (2)		Mortality (3)		In-hospital mortality (4)	
Timing								
Weekend	0.00	(1.7)	0.02	(3.4)**	−0.01	(1.4)	0.01	(0.2)
2nd quarter	−0.01	(2.2)**	−0.00	(0.4)	−0.02	(1.5)	0.08	(1.9)*
3rd quarter	−0.00	(1.1)	0.00	(0.6)	−0.00	(0.4)	0.04	(1.3)
4th quarter	−0.00	(1.2)	0.01	(0.8)	−0.00	(0.3)	0.08	(2.6)**
Comorbidities								
Recent AMI	−0.02	(4.5)***	0.02	(2.4)**	−0.03	(2.6)**	−0.00	(0.0)
Cardiovascular disease	0.04	(3.7)***	0.21	(13.9)***	0.04	(2.2)**	0.17	(2.5)**
Cerebrovascular disease	0.03	(3.1)**	0.14	(6.4)***	0.02	(0.9)	0.11	(1.0)
Gastrointestinal disease	0.02	(1.8)*	0.07	(4.0)***	0.06	(1.4)	−0.05	(0.3)
Diabetes	0.01	(1.8)*	0.06	(9.3)***	0.01	(0.7)	−0.06	(1.6)
Respiratory disease	0.02	(3.4)**	0.06	(4.7)***	0.02	(1.3)	−0.01	(0.1)
Cancer/AIDS	0.01	(1.9)*	0.13	(9.1)***	0.03	(1.2)	0.17	(1.3)
Other comorbidities	0.05	(4.2)***	0.19	(10.9)***	0.02	(1.0)	0.26	(2.5)**
Constant	0.22	(2.4)**	−0.11	(0.9)	0.30	(1.9)*	0.30	(0.5)
Observations	41,127		25,361		3,521		621	

Notes: Robust absolute t statistics clustered at the HSA level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table A2: Parameter Estimates Separate Processes – In-hospital Spending

	Locals				Visitors			
	Mortality	Hospital discharge	In-hospital mortality	Hospital transfer	Mortality	Hospital discharge	In-hospital mortality	Hospital transfer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Health-care spending								
In-hospital EOL ($\log T_g$)	−0.12 (1.9)*	0.21 (2.4)**	−0.75 (5.5)***	−0.31 (1.5)	−0.06 (0.4)	0.24 (2.4)**	−0.68 (2.4)**	−0.55 (2.5)**
Personal characteristics								
Age	0.07 (45.9)***	−0.01 (16.4)***	0.06 (16.3)***	−0.02 (10.6)***	0.06 (13.7)***	−0.01 (12.0)***	0.04 (5.4)***	−0.02 (9.2)***
Male	0.09 (3.9)***	0.02 (1.7)*	0.01 (0.2)	0.12 (6.8)***	0.18 (1.9)*	0.01 (0.5)	0.07 (0.4)	0.02 (0.2)
AMI of inferior wall (I21.1)	−0.20 (4.8)***	0.10 (6.0)***	−0.20 (2.9)**	0.08 (2.0)**	−0.20 (1.5)	0.08 (2.0)**	0.20 (0.9)	0.13 (1.7)*
AMI of other sites (I21.2)	−0.02 (0.2)	0.00 (0.1)	−0.28 (2.9)**	−0.02 (0.3)	0.19 (1.1)	0.03 (0.3)	−0.05 (0.1)	0.31 (1.3)
AMI of unspecified site (I21.3)	0.23 (3.2)**	−0.15 (4.4)***	0.30 (2.5)**	−0.62 (7.1)***	−0.01 (0.0)	−0.23 (2.4)**	0.03 (0.1)	−0.35 (1.4)
Non-ST elevation AMI (I21.4)	−0.09 (1.9)*	−0.11 (5.7)***	−1.19 (16.8)***	−0.25 (3.8)***	−0.30 (2.6)**	0.02 (0.4)	−1.41 (5.1)***	0.07 (0.4)
AMI, unspecified (I21.9)	0.07 (1.7)*	−0.24 (6.2)***	−0.02 (0.2)	−0.23 (2.2)**	−0.08 (0.7)	−0.13 (2.4)**	0.35 (1.9)*	−0.08 (0.6)
Length of stay	0.02 (8.6)***				0.02 (2.7)**			
Residence characteristics								
Median income 950€-1010€	−0.05 (1.0)	0.01 (0.3)	−0.06 (0.5)	0.13 (1.6)	−0.01 (0.1)	−0.08 (1.1)	0.14 (0.7)	0.22 (1.3)
Median income 1010€-1105€	−0.07 (1.4)	−0.01 (0.1)	0.01 (0.1)	0.07 (0.6)	0.04 (0.3)	−0.17 (2.3)**	0.40 (2.0)*	−0.00 (0.0)
Median income >1105€	0.03 (0.5)	0.01 (0.2)	0.08 (0.5)	0.40 (2.8)**	0.17 (1.3)	−0.17 (1.4)	0.81 (2.6)**	0.06 (0.3)
University educated	−0.01 (2.6)**	−0.01 (3.8)***	0.01 (1.6)	−0.03 (2.9)**	−0.02 (2.8)**	0.00 (0.5)	−0.02 (0.6)	−0.01 (1.0)
Rural area	0.00 (0.1)	−0.05 (2.8)**	0.01 (0.1)	−0.06 (1.2)	0.01 (0.1)	−0.02 (0.4)	−0.21 (1.0)	−0.16 (0.8)
Timing								
Weekend	0.06 (2.1)**	0.06 (7.7)***	0.12 (2.2)**	0.17 (8.0)***	0.10 (0.9)	0.11 (2.4)**	−0.20 (1.0)	0.15 (1.7)*
2nd quarter	−0.01 (0.3)	−0.02 (1.6)	−0.15 (2.8)**	−0.06 (2.2)**	0.12 (1.3)	0.00 (0.1)	−0.35 (1.3)	−0.08 (0.8)
3rd quarter	0.04 (1.1)	−0.02 (1.2)	−0.07 (1.2)	−0.04 (2.0)**	−0.02 (0.2)	−0.04 (1.1)	−0.11 (0.8)	−0.14 (1.4)
4th quarter	0.03 (1.1)	−0.01 (0.4)	−0.08 (1.2)	−0.01 (0.3)	−0.03 (0.4)	−0.01 (0.2)	0.01 (0.1)	−0.01 (0.1)
Comorbidities								
Recent AMI	0.10 (3.8)***	−0.00 (0.1)	−0.48 (6.2)***	−0.89 (16.7)***	0.13 (1.5)	−0.03 (0.6)	−0.71 (3.0)**	−1.00 (6.8)***
Cardiovascular disease	0.69 (19.7)***	−0.14 (9.5)***	0.44 (4.1)***	−0.23 (3.8)***	0.53 (5.0)***	−0.18 (3.3)***	0.53 (2.3)**	−0.51 (3.4)***
Cerebrovascular disease	0.42 (6.7)***	−0.15 (4.6)***	0.37 (3.1)**	−0.22 (3.4)***	0.66 (3.4)***	−0.07 (0.9)	0.35 (1.3)	−0.60 (2.0)**
Gastrointestinal disease	0.25 (3.8)***	−0.05 (1.5)	0.27 (2.5)**	−0.12 (1.6)	0.13 (0.6)	−0.25 (1.8)*	0.37 (0.9)	−0.88 (2.3)**
Diabetes	0.42 (15.3)***	−0.05 (4.4)***	0.18 (2.8)**	−0.00 (0.1)	0.33 (3.6)***	−0.07 (2.2)**	0.10 (0.5)	0.05 (0.7)
Respiratory disease	0.28 (6.6)***	−0.03 (1.9)*	0.29 (4.1)***	−0.07 (2.0)**	0.36 (2.5)**	−0.05 (1.2)	0.37 (1.8)*	−0.23 (1.4)

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Table A2 – Continued From Previous Page

	Locals								Visitors							
	Mortality (1)		Hospital discharge (2)		In-hospital mortality (3)		Hospital transfer (4)		Mortality (5)		Hospital discharge (6)		In-hospital mortality (7)		Hospital transfer (8)	
Cancer/AIDS	0.49	(11.7)***	−0.04	(2.1)**	0.20	(2.8)**	−0.07	(1.3)	1.09	(9.1)***	−0.18	(2.7)**	0.35	(1.3)	−0.39	(1.8)*
Other comorbidities	0.63	(12.5)***	−0.17	(4.6)***	0.47	(4.5)***	−0.27	(3.9)***	0.70	(3.7)***	−0.14	(2.0)**	0.04	(0.1)	−0.16	(0.7)
Duration dependence																
Constant	−10.25	(20.2)***	−2.12	(3.3)***	−0.85	(6.3)***	1.21	(0.8)	−10.58	(7.9)***	−2.63	(3.5)***	−1.38	(0.6)	3.16	(2.2)**
Duration 2	0.27	(2.8)**	0.23	(5.0)***	−2.43	(2.5)**	−0.23	(3.9)***	0.36	(1.3)	0.29	(5.4)***	−1.10	(4.9)***	−0.11	(0.7)
Duration 3	0.04	(0.4)	0.40	(5.9)***	−1.11	(20.2)***	−0.23	(2.0)**	0.46	(1.4)	0.52	(7.7)***	−1.23	(4.4)***	−0.10	(0.7)
Duration 4	−0.26	(3.0)**	0.33	(7.9)***	−1.12	(13.7)***	−0.29	(2.5)**	−0.01	(0.0)	0.39	(4.9)***	−1.14	(4.2)***	−0.12	(0.7)
Duration 5	−0.78	(8.8)***	0.08	(1.7)*	−1.07	(13.4)***	−0.90	(6.2)***	−0.40	(1.2)	0.15	(1.8)*	−1.22	(3.2)**	−0.61	(2.7)**
Duration 6	−1.20	(15.1)***	−0.29	(4.4)***	−1.05	(8.0)***	−2.06	(13.4)***	−0.68	(2.2)**	0.08	(0.6)	−0.55	(1.5)	−1.43	(3.4)***
Duration 7	−1.80	(21.4)***							−1.39	(4.9)***						
Duration 8	−2.30	(30.1)***							−1.98	(6.5)***						
-Log likelihood	217,285.9								18,672.6							
Observations	41,127								3,521							

Notes: Robust absolute t statistics clustered at the HSA level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table A3: Parameter Estimates Correlated Model – In-hospital Spending

	Locals								Visitors							
	Mortality (1)		Hospital discharge (2)		In-hospital mortality (3)		Hospital transfer (4)		Mortality (5)		Hospital discharge (6)		In-hospital mortality (7)		Hospital transfer (8)	
Health-care spending																
In-hospital EOL ($\log T_g$)	−0.14	(1.9)*	0.29	(2.0)**	−0.77	(3.7)***	−0.09	(0.4)	−0.10	(0.5)	0.31	(2.1)**	−0.72	(1.9)*	−0.34	(1.1)
Personal Characteristics																
Age	0.07	(31.4)***	−0.01	(7.4)***	0.06	(12.3)***	−0.02	(4.3)***	0.07	(8.7)***	−0.02	(7.6)***	0.04	(6.1)***	−0.03	(5.4)***
Male	0.10	(4.4)***	0.01	(0.9)	0.01	(0.2)	0.10	(2.8)**	0.21	(2.1)**	−0.00	(0.1)	0.01	(0.1)	−0.08	(0.8)
AMI of inferior wall (I21.1)	−0.22	(4.1)***	0.11	(4.2)***	−0.20	(2.6)**	0.12	(4.4)***	−0.29	(2.3)**	0.08	(1.3)	0.19	(0.8)	0.15	(1.2)
AMI of other sites (I21.2)	−0.04	(0.5)	−0.00	(0.0)	−0.29	(2.3)**	−0.04	(0.3)	0.16	(1.2)	0.02	(0.2)	−0.02	(0.0)	0.36	(1.4)
AMI of unspecified site (I21.3)	0.24	(3.2)**	−0.22	(1.9)*	0.33	(1.5)	−0.82	(3.8)***	0.01	(0.1)	−0.26	(2.8)**	−0.15	(0.3)	−0.45	(1.2)
Non-ST elevation AMI (I21.4)	−0.13	(3.4)***	−0.15	(3.0)**	−1.21	(11.6)***	−0.37	(2.3)**	−0.51	(4.0)***	−0.02	(0.4)	−1.56	(6.3)***	−0.05	(0.2)
AMI, unspecified (I21.9)	0.07	(1.5)	−0.30	(2.8)**	0.02	(0.1)	−0.43	(1.8)*	−0.12	(1.1)	−0.18	(2.1)**	0.40	(2.0)**	−0.29	(1.1)
Length of stay	0.02	(4.1)***							0.02	(2.2)**						
Residence characteristics																
Median income 950€-1010€	−0.04	(0.7)	−0.01	(0.1)	−0.04	(0.3)	0.08	(1.0)	−0.01	(0.1)	−0.08	(1.2)	0.07	(0.2)	0.24	(0.7)
Median income 1010€-1105€	−0.07	(1.3)	−0.02	(0.3)	−0.00	(0.0)	0.03	(0.2)	0.09	(0.4)	−0.21	(1.9)*	0.55	(1.6)	−0.11	(0.4)
Median income >1105€	0.04	(0.5)	−0.01	(0.1)	0.10	(0.4)	0.33	(1.3)	0.27	(1.1)	−0.23	(1.9)*	0.99	(1.8)*	−0.09	(0.3)
University educated	−0.01	(2.6)**	−0.01	(1.8)*	0.01	(1.4)	−0.03	(3.0)**	−0.03	(2.2)**	0.00	(0.4)	−0.03	(0.8)	−0.02	(0.8)
Rural area	−0.00	(0.0)	−0.07	(2.5)**	0.01	(0.2)	−0.13	(3.8)***	0.02	(0.1)	−0.03	(0.7)	−0.28	(1.1)	−0.20	(1.0)
Timing																
Weekend	0.08	(3.0)**	0.05	(2.3)**	0.16	(3.1)**	0.13	(2.0)**	0.12	(1.6)	0.06	(1.6)	−0.17	(0.7)	−0.01	(0.1)
2nd quarter	−0.01	(0.5)	−0.03	(1.9)*	−0.17	(2.4)**	−0.08	(2.7)**	0.05	(0.5)	0.01	(0.1)	−0.41	(1.5)	−0.07	(0.6)
3rd quarter	0.04	(1.3)	−0.02	(1.8)*	−0.07	(1.0)	−0.07	(2.5)**	−0.05	(0.4)	−0.08	(1.4)	−0.10	(0.6)	−0.23	(2.0)**
4th quarter	0.03	(1.0)	−0.02	(0.8)	−0.09	(1.3)	−0.03	(0.8)	−0.06	(0.5)	−0.00	(0.1)	−0.07	(0.3)	0.02	(0.1)
Comorbidities																
Recent AMI	0.10	(3.3)**	0.00	(0.1)	−0.49	(5.3)***	−0.87	(5.4)***	0.12	(1.1)	−0.05	(1.0)	−0.75	(3.0)**	−1.04	(3.4)***
Cardiovascular disease	0.75	(19.9)***	−0.14	(4.8)***	0.49	(3.7)***	−0.21	(2.2)**	0.86	(4.0)***	−0.23	(1.7)*	0.78	(2.3)**	−0.65	(1.1)
Cerebrovascular disease	0.46	(6.0)***	−0.17	(3.8)***	0.40	(2.9)**	−0.29	(2.6)**	0.81	(3.5)***	−0.07	(1.0)	0.22	(0.6)	−0.54	(1.8)*
Gastrointestinal disease	0.27	(3.9)***	−0.06	(1.4)	0.30	(2.4)**	−0.14	(1.8)*	−0.08	(0.3)	−0.30	(1.9)*	0.55	(1.4)	−1.08	(2.4)**
Diabetes	0.45	(18.7)***	−0.06	(3.6)***	0.20	(2.5)**	−0.02	(0.4)	0.33	(3.7)***	−0.06	(1.2)	0.08	(0.4)	0.06	(0.5)
Respiratory disease	0.30	(6.0)***	−0.03	(1.0)	0.30	(5.6)***	−0.05	(0.7)	0.49	(2.3)**	−0.12	(2.8)**	0.52	(1.9)*	−0.44	(2.6)**

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Table A3 – Continued From Previous Page

	Locals								Visitors							
	Mortality (1)		Hospital discharge (2)		In-hospital mortality (3)		Hospital transfer (4)		Mortality (5)		Hospital discharge (6)		In-hospital mortality (7)		Hospital transfer (8)	
Cancer/AIDS	0.52	(11.3)***	−0.03	(0.9)	0.17	(2.3)**	−0.02	(0.2)	1.48	(6.5)***	−0.22	(2.1)**	0.65	(1.5)	−0.45	(1.8)*
Other comorbidities	0.69	(12.4)***	−0.19	(3.6)***	0.52	(4.4)***	−0.34	(3.2)**	0.88	(4.6)***	−0.16	(1.6)	0.17	(0.5)	−0.25	(0.7)
Duration dependence																
Duration 2	0.27	(2.7)**	0.45	(5.9)***	−1.26	(16.4)***	0.31	(3.6)***	0.36	(1.2)	0.54	(6.5)***	−1.11	(4.2)***	0.51	(2.8)**
Duration 3	0.04	(0.4)	0.83	(5.5)***	−1.39	(11.0)***	0.98	(3.4)***	0.47	(1.3)	0.97	(6.9)***	−1.26	(3.6)***	1.34	(2.4)**
Duration 4	−0.24	(3.0)**	0.93	(7.0)***	−1.41	(11.3)***	1.85	(5.1)***	0.03	(0.1)	0.96	(7.9)***	−1.16	(3.7)***	1.95	(7.0)***
Duration 5	−0.76	(8.6)***	0.72	(6.1)***	−1.37	(6.4)***	1.63	(11.9)***	−0.33	(1.0)	0.74	(7.5)***	−1.11	(2.2)**	1.64	(7.1)***
Duration 6	−1.16	(13.7)***	0.36	(3.3)***	−1.02	(2.6)**	−3.33	(15.8)***	−0.56	(1.8)*	0.68	(4.0)***	−0.21	(0.4)	0.85	(2.4)**
Duration 7	−1.75	(18.2)***							−1.21	(4.4)***						
Duration 8	−2.21	(22.5)***							−1.61	(4.9)***						
Unobserved heterogeneity																
Constant ($\nu_1, \upsilon_{s,1}, \upsilon_{h,1}, \upsilon_{r,1}$)	−10.63	(20.2)***	−2.06	(1.9)*	−4.85	(2.7)**	0.79	(0.5)	−12.53	(6.6)***	−2.27	(1.8)*	−2.59	(0.7)	3.23	(1.3)
ν_2	0.99	(3.6)***							2.04	(5.4)***						
$\upsilon_{s,2}$			−1.15	(10.3)***							−1.26	(8.4)***				
$\upsilon_{h,2}$					3.40	(3.2)**							2.70	(2.4)**		
$\upsilon_{r,2}$							0.50	(3.2)**							−3.29	(8.1)***

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Table A3 – Continued From Previous Page

	Locals				Visitors			
	Mortality	Hospital discharge	In-hospital mortality	Hospital transfer	Mortality	Hospital discharge	In-hospital mortality	Hospital transfer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α_1		0.59	(1.2)			−0.17	(0.3)	
α_2		$-\infty$				−0.52	(1.0)	
α_{11}		−0.30	(0.6)			0.14	(0.2)	
α_{12}		$-\infty$				−0.25	(0.2)	
α_{15}		−0.43	(0.3)			$-\infty$		
-Log likelihood		215,462.9				18,522.9		
Observations		41,127				3,521		

Notes: Robust absolute t statistics clustered at the HSA level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table A4: Parameter Estimates Separate Processes – Post-discharge Spending

	Stayers				Movers			
	Mortality (1)	Hospital discharge (2)	In-hospital mortality (3)	Hospital transfer (4)	Mortality (5)	Hospital discharge (6)	In-hospital mortality (7)	Hospital transfer (8)
Health-care spending								
In-hospital EOL ($\log T_g$)	−0.29 (2.0)**	0.21 (2.5)**	−0.72 (5.2)***	−0.34 (1.8)*	−0.92 (1.9)*	0.09 (0.5)	−1.77 (2.7)**	−0.35 (1.7)*
Personal characteristics								
Age	0.07 (44.2)***	−0.01 (16.4)***	0.05 (17.9)***	−0.02 (11.9)***	0.07 (7.4)***	−0.01 (5.8)***	0.06 (2.2)**	−0.02 (2.9)**
Male	0.10 (4.0)***	0.02 (1.7)*	0.02 (0.4)	0.12 (7.1)***	0.05 (0.3)	0.08 (1.8)*	−0.49 (1.0)	−0.10 (1.0)
AMI of inferior wall (I21.1)	−0.21 (4.7)***	0.10 (6.0)***	−0.17 (2.8)**	0.09 (2.3)**	−0.12 (0.4)	0.22 (2.7)**	−0.10 (0.1)	0.19 (1.4)
AMI of other sites (I21.2)	0.00 (0.0)	0.02 (0.6)	−0.26 (2.9)**	0.00 (0.0)	−0.45 (1.5)	−0.15 (1.0)	−0.72 (0.5)	0.03 (0.1)
AMI of unspecified site (I21.3)	0.20 (3.0)**	−0.16 (4.5)***	0.29 (2.5)**	−0.59 (7.5)***	−0.01 (0.0)	−0.07 (0.4)	0.80 (0.9)	−0.78 (1.3)
Non-ST elevation AMI (I21.4)	−0.10 (2.3)**	−0.10 (5.6)***	−1.20 (19.3)***	−0.22 (3.3)**	−0.17 (1.1)	−0.03 (0.3)	−1.50 (1.5)	−0.31 (1.6)
AMI, unspecified (I21.9)	0.09 (2.2)**	−0.23 (6.5)***	0.03 (0.4)	−0.22 (2.2)**	−0.29 (1.1)	−0.24 (1.9)*	−0.02 (0.0)	−0.31 (1.2)
Length of stay	0.02 (9.3)***				0.00 (0.1)			
Residence characteristics								
Median income 950€-1010€	−0.03 (0.7)	0.01 (0.3)	−0.05 (0.5)	0.14 (1.9)*	0.15 (0.6)	0.04 (0.4)	0.54 (0.8)	0.24 (1.4)
Median income 1010€-1105€	−0.05 (1.0)	−0.01 (0.2)	0.04 (0.3)	0.08 (0.7)	0.42 (1.8)*	−0.03 (0.2)	0.41 (0.6)	−0.02 (0.1)
Median income >1105€	0.07 (1.4)	−0.00 (0.0)	0.16 (1.1)	0.38 (2.9)**	0.30 (1.0)	−0.07 (0.5)	0.69 (1.1)	0.33 (1.5)
University	−0.01 (3.9)***	−0.01 (4.1)***	0.01 (1.4)	−0.02 (2.9)**	−0.01 (1.3)	0.00 (0.1)	−0.03 (0.9)	−0.03 (1.4)
Rural area	−0.00 (0.1)	−0.04 (2.8)**	−0.02 (0.3)	−0.05 (1.1)	0.37 (1.9)*	−0.10 (1.2)	−0.29 (0.7)	−0.33 (1.4)
Timing								
Weekend	0.07 (2.5)**	0.07 (8.0)***	0.09 (1.9)*	0.17 (8.6)***	−0.17 (1.0)	−0.04 (0.7)	0.40 (0.9)	−0.07 (0.5)
2nd quarter	−0.00 (0.1)	−0.02 (1.7)*	−0.17 (3.6)***	−0.07 (2.3)**	0.20 (1.0)	0.01 (0.2)	0.29 (0.4)	0.15 (0.9)
3rd quarter	0.03 (1.0)	−0.02 (1.4)	−0.08 (1.5)	−0.05 (2.3)**	−0.03 (0.1)	−0.03 (0.4)	0.59 (0.8)	−0.01 (0.1)
4th quarter	0.02 (0.9)	−0.01 (0.6)	−0.07 (1.1)	−0.01 (0.3)	0.10 (0.5)	0.03 (0.5)	0.33 (0.4)	−0.14 (0.8)
Comorbidities								
Recent AMI	0.11 (3.9)***	−0.01 (0.3)	−0.50 (7.2)***	−0.90 (17.9)***	0.15 (1.2)	−0.02 (0.3)	−0.67 (0.9)	−0.86 (2.6)**
Cardiovascular disease	0.67 (17.3)***	−0.15 (10.6)***	0.44 (4.3)***	−0.26 (4.2)***	0.95 (4.7)***	−0.11 (0.7)	1.02 (2.3)**	−0.35 (1.2)
Cerebrovascular disease	0.44 (6.8)***	−0.14 (4.8)***	0.40 (3.6)***	−0.25 (3.8)***	0.74 (2.5)**	−0.19 (2.0)**	−0.72 (0.6)	−0.48 (1.2)
Gastrointestinal disease	0.25 (3.7)***	−0.06 (2.1)**	0.27 (2.3)**	−0.14 (1.9)*	−0.44 (0.7)	0.12 (1.0)	0.61 (0.6)	−1.18 (1.2)
Diabetes	0.42 (15.4)***	−0.06 (5.0)***	0.17 (2.7)**	0.00 (0.1)	0.27 (1.6)	0.02 (0.3)	0.09 (0.1)	0.00 (0.0)
Respiratory disease	0.28 (6.8)***	−0.03 (2.2)**	0.28 (4.1)***	−0.08 (2.3)**	0.09 (0.4)	0.01 (0.1)	1.29 (2.7)**	0.21 (1.3)

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Table A4 – Continued From Previous Page

	Stayers								Movers							
	Mortality (1)		Hospital discharge (2)		In-hospital mortality (3)		Hospital transfer (4)		Mortality (5)		Hospital discharge (6)		In-hospital mortality (7)		Hospital transfer (8)	
Cancer/AIDS	0.53	(12.7)***	−0.05	(2.7)**	0.21	(3.0)**	−0.09	(1.6)	1.13	(1.9)*	−0.12	(0.4)	0.69	(0.7)	−0.42	(0.9)
Other comorbidities	0.63	(11.4)***	−0.17	(4.7)***	0.45	(4.2)***	−0.26	(3.9)***	1.24	(3.5)***	−0.28	(2.0)**	0.87	(1.3)	−0.38	(1.2)
Duration dependence																
Constant	−9.50	(11.9)***	−2.12	(3.5)***	−0.78	(5.9)***	1.41	(1.0)	−7.85	(3.1)**	−1.45	(1.0)	4.63	(1.0)	1.80	(1.1)
Duration 2	0.26	(2.8)**	0.23	(5.2)***	−2.42	(2.4)**	−0.22	(3.8)***	1.61	(1.5)	0.24	(3.8)***	−1.06	(2.1)**	−0.36	(2.0)*
Duration 3	0.06	(0.6)	0.41	(6.2)***	−1.10	(20.1)***	−0.22	(2.0)**	1.27	(1.2)	0.34	(3.4)***	−2.00	(2.2)**	−0.14	(0.6)
Duration 4	−0.24	(2.9)**	0.34	(7.9)***	−1.12	(14.3)***	−0.28	(2.5)**	0.27	(0.2)	0.26	(2.3)**	−2.01	(1.8)*	−0.39	(1.2)
Duration 5	−0.77	(8.6)***	0.09	(2.1)**	−1.06	(13.8)***	−0.87	(6.6)***	0.43	(0.5)	−0.23	(1.4)			−1.44	(2.3)**
Duration 6	−1.17	(14.1)***	−0.27	(4.2)***	−1.03	(9.1)***	−2.04	(14.6)***	0.14	(0.1)	0.04	(0.2)			−1.27	(1.6)
Duration 7	−1.79	(21.0)***							−0.42	(0.4)						
Duration 8	−2.30	(30.3)***							−0.65	(0.7)						
-Log likelihood	230,457.8								5,579.5							
Observations	43,510								1,138							

Notes: Robust absolute t statistics clustered at the HSA level in parentheses. Duration dependence parameters for durations 5 and 6 not estimated due to insufficient number of events in movers' in-hospital mortality equation.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table A5: Parameter Estimates Correlated Model – Post-discharge Spending

	Stayers								Movers							
	Mortality (1)		Hospital discharge (2)		In-hospital mortality (3)		Hospital transfer (4)		Mortality (5)		Hospital discharge (6)		In-hospital mortality (7)		Hospital transfer (8)	
Health-care spending																
Post-discharge ($\log T_g^P$)	−0.28	(3.1)**	0.28	(15.4)***	−0.72	(9.3)***	−0.12	(3.0)**	−0.97	(1.9)*	0.20	(1.0)	−1.79	(2.6)**	−0.11	(0.3)
Personal Characteristics																
Age	0.07	(52.0)***	−0.01	(27.6)***	0.05	(22.0)***	−0.02	(17.8)***	0.07	(6.9)***	−0.01	(4.3)***	0.06	(2.1)**	−0.01	(1.9)*
Male	0.10	(4.4)***	0.01	(0.8)	0.03	(0.6)	0.09	(3.4)***	0.02	(0.1)	0.12	(2.1)**	−0.48	(1.0)	0.02	(0.1)
AMI of inferior wall (I21.1)	−0.22	(6.2)***	0.11	(6.7)***	−0.16	(2.4)**	0.12	(3.6)***	−0.14	(0.5)	0.24	(2.5)**	−0.10	(0.1)	0.23	(1.1)
AMI of other sites (I21.2)	−0.02	(0.3)	0.01	(0.4)	−0.28	(2.3)**	−0.01	(0.2)	−0.48	(1.3)	−0.13	(0.5)	−0.78	(0.6)	−0.02	(0.0)
AMI of unspecified site (I21.3)	0.22	(3.6)***	−0.22	(6.2)***	0.31	(2.9)**	−0.79	(8.5)***	−0.03	(0.1)	−0.27	(1.1)	0.91	(1.0)	−1.39	(3.0)**
Non-ST elevation AMI (I21.4)	−0.14	(4.3)***	−0.15	(9.5)***	−1.21	(16.5)***	−0.35	(10.4)***	−0.17	(1.0)	−0.12	(1.1)	−1.54	(1.6)	−0.63	(3.0)**
AMI, unspecified (I21.9)	0.09	(2.4)**	−0.30	(14.9)***	0.05	(0.8)	−0.43	(9.7)***	−0.30	(1.1)	−0.37	(2.8)**	−0.07	(0.1)	−0.78	(2.7)**
Length of stay	0.02	(8.2)***							−0.01	(0.3)						
Residence characteristics																
Median income 950€-1010€	−0.02	(0.7)	−0.01	(0.6)	−0.04	(0.5)	0.09	(2.5)**	0.18	(0.7)	0.04	(0.4)	0.57	(0.8)	0.31	(1.4)
Median income 1010€-1105€	−0.05	(1.3)	−0.02	(1.5)	0.04	(0.5)	0.03	(0.9)	0.46	(1.8)*	−0.08	(0.6)	0.43	(0.7)	−0.17	(0.5)
Median income >1105€	0.08	(1.8)*	−0.02	(1.0)	0.17	(1.9)*	0.32	(7.1)***	0.34	(1.1)	−0.07	(0.4)	0.80	(1.3)	0.41	(1.1)
University	−0.01	(4.6)***	−0.01	(8.5)***	0.01	(1.8)*	−0.03	(10.1)***	−0.02	(1.5)	−0.00	(0.1)	−0.03	(1.0)	−0.03	(1.5)
Rural area	−0.01	(0.3)	−0.06	(3.7)***	−0.02	(0.3)	−0.11	(3.3)***	0.39	(1.9)*	−0.09	(1.1)	−0.33	(0.7)	−0.30	(1.2)
Timing																
Weekend	0.09	(3.3)***	0.05	(4.0)***	0.13	(2.4)**	0.13	(4.7)***	−0.16	(1.0)	−0.08	(1.1)	0.34	(0.8)	−0.18	(0.9)
2nd quarter	−0.01	(0.3)	−0.02	(1.5)	−0.18	(2.7)**	−0.08	(2.3)**	0.21	(0.9)	0.01	(0.1)	0.31	(0.4)	0.11	(0.5)
3rd quarter	0.03	(1.1)	−0.03	(1.8)*	−0.07	(1.1)	−0.08	(2.3)**	−0.01	(0.0)	−0.03	(0.3)	0.55	(0.7)	−0.02	(0.1)
4th quarter	0.02	(0.8)	−0.02	(1.1)	−0.07	(1.1)	−0.03	(0.8)	0.13	(0.6)	−0.01	(0.2)	0.29	(0.3)	−0.28	(2.0)**
Comorbidities																
Recent AMI	0.10	(3.6)***	−0.00	(0.1)	−0.51	(7.1)***	−0.88	(21.0)***	0.15	(1.1)	0.01	(0.2)	−0.70	(0.9)	−0.74	(1.8)*
Cardiovascular disease	0.72	(20.2)***	−0.15	(6.0)***	0.47	(6.3)***	−0.25	(4.1)***	0.98	(4.6)***	−0.05	(0.3)	1.16	(2.0)**	−0.20	(0.5)
Cerebrovascular disease	0.47	(8.8)***	−0.16	(4.2)***	0.41	(3.9)***	−0.30	(3.2)**	0.78	(2.5)**	−0.20	(1.8)*	−0.83	(0.7)	−0.47	(0.9)
Gastrointestinal disease	0.27	(4.2)***	−0.07	(1.8)*	0.28	(2.2)**	−0.16	(1.7)*	−0.48	(0.7)	0.04	(0.2)	0.54	(0.5)	−1.37	(1.1)
Diabetes	0.44	(18.2)***	−0.06	(4.7)***	0.18	(3.5)***	−0.01	(0.4)	0.28	(1.6)	0.01	(0.1)	0.06	(0.1)	0.07	(0.4)
Respiratory disease	0.30	(8.4)***	−0.04	(1.7)*	0.29	(3.9)***	−0.08	(1.6)*	0.12	(0.5)	−0.06	(0.5)	1.22	(2.5)**	−0.05	(0.2)

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Table A5 – Continued From Previous Page

	Stayers								Movers							
	Mortality (1)		Hospital discharge (2)		In-hospital mortality (3)		Hospital transfer (4)		Mortality (5)		Hospital discharge (6)		In-hospital mortality (7)		Hospital transfer (8)	
Cancer/AIDS	0.57	(13.3)***	−0.04	(1.4)	0.19	(1.9)*	−0.04	(0.6)	1.19	(1.8)*	−0.15	(0.6)	0.62	(0.6)	−0.46	(1.0)
Other comorbidities	0.68	(15.4)***	−0.19	(5.7)***	0.46	(5.1)***	−0.32	(4.0)***	1.32	(3.9)***	−0.39	(1.8)*	0.84	(1.2)	−0.82	(1.6)
Duration dependence																
Duration 2	0.26	(2.7)**	0.46	(32.7)***	−1.27	(18.6)***	0.32	(11.6)***	1.62	(1.5)	0.38	(6.0)***	−1.02	(2.1)**	0.01	(0.1)
Duration 3	0.07	(0.7)	0.84	(44.6)***	−1.41	(16.3)***	0.99	(21.0)***	1.28	(1.2)	0.63	(6.2)***	−1.92	(2.0)**	0.70	(2.8)**
Duration 4	−0.22	(2.7)**	0.94	(44.5)***	−1.43	(15.5)***	1.86	(28.6)***	0.28	(0.2)	0.72	(5.8)***	−1.88	(1.7)*	1.23	(3.3)***
Duration 5	−0.74	(8.8)***	0.73	(24.8)***	−1.40	(10.4)***	1.64	(18.3)***	0.46	(0.5)	0.36	(1.8)*	−3000	(.)	1.64	(2.2)**
Duration 6	−1.13	(13.8)***	0.38	(9.8)***	−1.06	(6.5)***	−3.32	(63.2)***	0.19	(0.2)	0.66	(2.9)**	−3000	(.)	2.35	(1.8)*
Duration 7	−1.73	(21.9)***							−0.34	(0.3)						
Duration 8	−2.19	(27.6)***							−0.49	(0.5)						
Unobserved heterogeneity																
Constant ($\nu_1, \upsilon_{s,1}, \upsilon_{h,1}, \upsilon_{r,1}$)	−10.09	(19.8)***	−2.02	(14.1)***	−5.29	(4.4)***	1.03	(3.3)***	−7.98	(3.0)**	−1.96	(1.2)	4.84	(0.9)	0.56	(0.2)
ν_2	1.10	(7.0)***							1.40	(3.3)***						
$\upsilon_{s,2}$			−1.16	(65.3)***							−0.96	(10.1)***				
$\upsilon_{h,2}$					3.65	(3.5)***							$-\infty$			
$\upsilon_{r,2}$							0.49	(3.1)**							−4.36	(3.4)***
α_1				0.72	(3.6)***							1.77	(2.4)**			
α_{11}				−0.54	(1.2)							1.18	(1.1)			
α_{15}				0.22	(0.5)							$-\infty$				
-Log likelihood					228,517.8								5536.6			
Observations					43,510								1,138			

Notes: Robust absolute t statistics clustered at the HSA level in parentheses. Duration dependence parameters for durations 5 and 6 not estimated due to insufficient number of events in movers' in-hospital mortality equation.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table A6: Descriptive Statistics by Quartile of Spending Intensity for Locals/Visitors

Patient group	Locals				Visitors			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Health-care spending								
In-hospital EOL ($\log T_g$)	7.144	7.467*	7.809*	8.017*	7.176	7.444*	7.744*	8.019*
Outcome								
In-hospital mortality	0.072	0.042	0.025*	0.043*	0.091	0.046*	0.036*	0.042*
Post-discharge mortality	0.308	0.247	0.233*	0.228*	0.300	0.269	0.267	0.237*
Observed duration[1]	700.6	771.8	847.0*	776.3*	616.2	733.7*	752.1*	685.0*
Length of stay[1]	5.8	5.8	5.1	5.1	6.2	6.2	5.6	5.1*
Personal characteristics								
Age	69.0	67.5	66.5*	66.2*	67.6	66.2	65.8	63.7*
Male	0.565	0.623*	0.638*	0.661*	0.608	0.618	0.648	0.670
AMI of anterior wall (I21.0)	0.192	0.221	0.208	0.278*	0.201	0.208	0.223	0.266
AMI of inferior wall (I21.1)	0.183	0.233	0.232	0.290	0.176	0.185	0.164	0.299
AMI of other sites (I21.2)	0.039	0.050	0.051	0.039	0.028	0.029	0.020	0.036
AMI of unspecified site (I21.3)	0.017	0.020	0.066*	0.017	0.022	0.027	0.066*	0.011
Non-ST elevation AMI (I21.4)	0.388	0.307	0.346	0.273*	0.337	0.356	0.434	0.303
AMI, unspecified (I21.9)	0.180	0.168	0.097	0.102	0.235	0.195	0.093*	0.085*
Residence characteristics								
Median income	967.5	1012.7	1020.0*	1123.7	1001.5	1018.0	975.5	963.6
University educated	0.129	0.141	0.151*	0.199*	0.145	0.139	0.129	0.112*
Rural area	0.310	0.316	0.247*	0.193*	0.252	0.350	0.252	0.454*
Comorbidities								
Charlson index	0.998	0.879	0.959	0.811*	0.980	0.873	1.091	0.978
Recent AMI	0.160	0.144	0.208*	0.169	0.171	0.134	0.244	0.216
Cardiovascular disease	0.068	0.053	0.068	0.050*	0.078	0.069	0.109*	0.058
Cerebrovascular disease	0.032	0.022*	0.025	0.018*	0.030	0.034	0.036	0.029
Gastrointestinal disease	0.023	0.020	0.017	0.020	0.018	0.015	0.013	0.019
Diabetes	0.262	0.239	0.242	0.221*	0.263	0.226	0.244	0.238
Respiratory disease	0.082	0.076	0.079	0.065*	0.083	0.081	0.086	0.076
Cancer/AIDS	0.049	0.043	0.042	0.040*	0.036	0.047	0.041	0.042
Other comorbidities	0.044	0.029*	0.037	0.027*	0.042	0.027	0.039	0.041

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Table A6 – Continued From Previous Page

Patient group	Locals				Visitors			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Timing								
Weekend	0.236	0.229	0.213*	0.235	0.257	0.260	0.215*	0.222*
1st quarter	0.241	0.234	0.232	0.228*	0.245	0.212	0.233	0.211
2nd quarter	0.234	0.248*	0.240	0.239	0.237	0.253	0.250	0.240
3rd quarter	0.252	0.250	0.261	0.254	0.249	0.266	0.258	0.239
4th quarter	0.273	0.268	0.267	0.279	0.269	0.269	0.259	0.309*
Observations	10,840	10,227	9,879	10,181	919	655	861	1,086

Notes: * Significantly different from bottom quartile at the 5-percent level. Standard errors clustered at the HSA level.
[1] Reported in days.

Table A7: Descriptive Statistics by Quartile of Spending Intensity for Movers/Stayers

Patient group	Stayers				Movers			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Health-care spending								
Post-discharge ($\log T_g^P$)	5.434	5.624*	5.716*	5.790*	5.446	5.623*	5.719*	5.789*
Outcome								
In-hospital mortality	0.043	0.054	0.054	0.034	0.023	0.022	0.017	0.027
Post-discharge mortality	0.254	0.274	0.258	0.236	0.203	0.196	0.182	0.203
Observed duration[1]	767.6	750.9	759.6	791.6	783.5	797.2	838.9	766.3
Length of stay[1]	5.3	5.6	5.6	5.4	5.3	5.5	5.9	5.8
Personal characteristics								
Age	66.8	67.6	67.8*	66.8	64.1	62.9	65.6	64.0
Male	0.605	0.615	0.637	0.636	0.641	0.717	0.600	0.649
AMI of anterior wall (I21.0)	0.206	0.224	0.238	0.236	0.188	0.246	0.249*	0.257
AMI of inferior wall (I21.1)	0.219	0.229	0.241	0.245	0.219	0.227	0.225	0.284
AMI of other sites (I21.2)	0.034	0.052	0.040	0.053	0.055	0.050	0.039	0.027
AMI of unspecified site (I21.3)	0.033	0.027	0.025	0.035	0.031	0.031	0.034	0.020
Non-ST elevation AMI (I21.4)	0.392	0.334	0.303*	0.274*	0.418	0.299*	0.269*	0.277*
AMI, unspecified (I21.9)	0.116	0.134	0.154	0.157	0.090	0.146	0.184*	0.135
Residence characteristics								
Median income	956.3	1003.4	1121.1*	1022.6*	961.6	993.7	1153.6*	1040.1*
University	0.142	0.136	0.184	0.144	0.143	0.132	0.203*	0.142
Rural area	0.268	0.308	0.198*	0.342*	0.281	0.361	0.194*	0.365
Comorbidities								
Charlson index	0.936	0.960	0.888	0.894	0.816	0.692	0.799	0.872
Recent AMI	0.159	0.185	0.166	0.180	0.176	0.168	0.199	0.135
Cardiovascular disease	0.073	0.063	0.056*	0.049*	0.078	0.040	0.044	0.054
Cerebrovascular disease	0.028	0.027	0.022*	0.021*	0.043	0.022	0.036	0.020
Gastrointestinal disease	0.018	0.019	0.018	0.031*	0.008	0.019	0.007	0.020
Diabetes	0.247	0.240	0.242	0.237	0.195	0.193	0.223	0.270
Respiratory disease	0.092	0.075*	0.063*	0.076	0.082	0.047	0.044*	0.034*
Cancer/AIDS	0.040	0.050*	0.041	0.046	0.016	0.006	0.027	0.041
Other comorbidities	0.035	0.032	0.034	0.040	0.031	0.034	0.031	0.034

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Table A7 – Continued From Previous Page

Patient group	Stayers				Movers			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Timing								
Weekend	0.232	0.228	0.227	0.227	0.262	0.243	0.237	0.236
1st quarter	0.235	0.236	0.233	0.227	0.242	0.224	0.218	0.236
2nd quarter	0.235	0.241	0.241	0.244	0.246	0.249	0.269	0.230
3rd quarter	0.253	0.256	0.252	0.257	0.227	0.268	0.220	0.284
4th quarter	0.277	0.267	0.273	0.272	0.285	0.259	0.293	0.250
Observations	12,390	11,819	12,014	7,287	256	321	413	148

Notes: * Significantly different from bottom quartile at the 5-percent level. Standard errors clustered at the HSA level.
[1] Reported in days.

Appendix B

B.1 Magnitude of effects

For an exponential MPH model, the survivor function S is given by $S(s \mid x, t, u) = \exp(-\int_0^t \theta(s \mid x, t, u)\, ds$, with $\theta = \lambda(t) \exp(x'\beta + u)$, where $\lambda(t)$ denotes the duration dependence. The predicted survival probabilities are then obtained by calculating the linear predictor $x'\beta$ using the estimated coefficients (including the duration dependence) set at given values of explanatory variables and averaged over the unobserved heterogeneity distribution. For spending effects, we assume a median-aged 67-year old male (sample median), hospitalized for 5 days (sample median) with ST elevation myocardial infarction of anterior wall during the first quarter of year, with two most common comorbidities – diabetes and and cardiovascular disease. We also assume that this individual neither had a PCI intervention nor a surgery and was not hospitalized during weekend. The residence of this patient was in metropolitan area and in the highest income bracket. The spending predictor is then varied based on percentiles of spending distribution. The same patient is then assumed for the simulation of the age effects, except that the age is varied based on percentiles of the age distribution, while spending is fixed at a median-spending HSA.

Appendix C

C.1 Districts in Slovakia

Table C1: Districts in Slovakia

District	Code	Region	Population	Area (km^2)	Population density	Number of municipalities
Bánovce nad Bebravou	BN	Trenčiansky	35,658	461.9	77	43
Banská Bystrica	BB	Banskobystrický	108,120	809.4	134	42
Banská Štiavnica	BS	Banskobystrický	15,551	292.3	53	15
Bardejov	BJ	Prešovský	75,786	936.2	81	86
Bratislava I	BA I	Bratislavský	46,432	9.6	4,842	
Bratislava II	BA II	Bratislavský	125,001	92.5	1,352	
Bratislava III	BA III	Bratislavský	76,694	74.7	1,027	
Bratislava IV	BA IV	Bratislavský	105,154	96.7	1,087	
Bratislava V	BA V	Bratislavský	122,296	94.2	1,298	
Brezno	BR	Banskobystrický	58,965	1,265.2	47	30
Bytča	BY	Žilinský	31,163	281.6	111	12
Čadca	CA	Žilinský	87,969	760.6	116	23
Detva	DT	Banskobystrický	30,854	449.2	69	15
Dolný Kubín	DK	Žilinský	38,937	491.9	79	24
Dunajská Streda	DS	Trnavský	125,238	1,074.6	117	67
Galanta	GA	Trnavský	95,027	641.7	148	36
Gelnica	GL	Košický	31,668	584.4	54	20
Hlohovec	HC	Trnavský	43,769	267.2	164	24
Humenné	HE	Prešovský	59,535	754.2	79	62
Ilava	IL	Trenčiansky	57,511	358.5	160	21
Kežmarok	KK	Prešovský	74,232	839.3	88	41
Komárno	KN	Nitriansky	100,212	1,100.1	91	41
Košice I	KE I	Košický	63,904	85.4	748	
Košice II	KE II	Košický	79,034	73.9	1,070	
Košice III	KE III	Košický	27,924	16.9	1,657	
Košice IV	KE IV	Košický	56,596	60.9	929	
Košice-okolie	KS	Košický	129,237	1,541.3	84	114
Krupina	KA	Banskobystrický	21,366	584.9	37	36
Kysucké Nové Mesto	KM	Žilinský	32,654	173.7	188	14

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TABLE C1 – CONTINUED FROM PREVIOUS PAGE

District	Code	Region	Population	Area (km^2)	Population density	Number of municipalities
Levice	LV	Nitriansky	109,588	1,551.1	71	89
Levoča	LE	Prešovský	33,127	357.3	93	33
Liptovský Mikuláš	LM	Žilinský	71,685	1,341.1	53	56
Lučenec	LC	Banskobystrický	69,788	825.6	85	57
Malacky	MA	Bratislavský	78,809	949.5	83	26
Martin	MT	Žilinský	93,816	735.7	128	43
Medzilaborce	ML	Prešovský	10,870	427.3	25	23
Michalovce	MI	Košický	108,520	1,019.3	106	78
Myjava	MY	Trenčiansky	25,363	327.4	77	17
Námestovo	NO	Žilinský	63,563	690.5	92	24
Nitra	NR	Nitriansky	164,580	870.7	189	62
Nové Mesto nad Váhom	NM	Trenčiansky	61,512	580.0	106	34
Nové Zámky	NZ	Nitriansky	137,001	1,347.1	102	62
Partizánske	PE	Trenčiansky	44,179	301.0	147	23
Pezinok	PK	Bratislavský	69,623	375.5	185	17
Piešťany	PN	Trnavský	62,662	381.1	164	27
Poltár	PT	Banskobystrický	20,427	476.2	43	22
Poprad	PP	Prešovský	102,469	1,105.4	93	29
Považská Bystrica	PB	Trenčiansky	61,211	463.2	132	28
Prešov	PO	Prešovský	173,187	933.7	185	91
Prievidza	PD	Trenčiansky	130,616	959.8	136	52
Púchov	PU	Trenčiansky	44,133	375.3	118	21
Revúca	RA	Banskobystrický	38,242	730.3	52	42
Rimavská Sobota	RS	Banskobystrický	80,359	1,471.1	55	107
Rožňava	RV	Košický	58,995	1,173.3	50	62
Ružomberok	RK	Žilinský	57,036	646.8	88	25
Sabinov	SB	Prešovský	60,607	483.5	125	43
Senec	SC	Bratislavský	99,705	359.9	277	29
Senica	SE	Trnavský	59,347	683.5	87	31
Skalica	SI	Trnavský	47,313	357.1	132	21
Snina	SV	Prešovský	34,655	804.7	43	34
Sobrance	SO	Košický	22,377	538.2	42	47
Spišská Nová Ves	SN	Košický	98,656	587.4	168	36
Stará Ľubovňa	SL	Prešovský	52,867	624.0	85	44

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Table C1 – Continued From Previous Page

District	Code	Region	Population	Area (km^2)	Population density	Number of municipalities
Stropkov	SP	Prešovský	19,744	389.0	51	43
Svidník	SK	Prešovský	31,397	549.8	57	68
Šaľa	SA	Nitriansky	50,972	355.9	143	13
Topoľčany	TO	Nitriansky	70,313	597.6	118	54
Trebišov	TV	Košický	103,377	1,073.5	96	82
Trenčín	TN	Trenčiansky	113,516	674.8	168	37
Trnava	TT	Trnavský	131,940	741.3	178	45
Turčianske Teplice	TR	Žilinský	15,848	392.8	40	26
Tvrdošín	TS	Žilinský	35,802	478.9	75	15
Veľký Krtíš	VK	Banskobystrický	41,605	848.2	49	71
Vranov nad Topľou	VT	Prešovský	79,181	769.5	103	68
Zlaté Moravce	ZM	Nitriansky	40,881	521.2	78	33
Zvolen	ZV	Banskobystrický	66,294	759.0	87	26
Žarnovica	ZC	Banskobystrický	24,991	425.3	59	18
Žiar nad Hronom	ZH	Banskobystrický	44,424	517.7	86	35
Žilina	ZA	Žilinský	161,052	815.1	198	53

Notes: Based on data from the Statistical Office of the Slovak Republic.