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Vogelpothsweg 87, 44227 Dortmund, Germany

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

Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI)
Hohenzollernstr. 1-3, 45128 Essen, Germany

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Adam Pilny and Roman Mennicken[1]

Does Hospital Reputation Influence the Choice of Hospital?

Abstract

A number of recent empirical studies document significant effects of in-patient care quality indicators on the choice of hospital. These studies use either objective quality indicators based on quantitative figures, or if subjective reputation scores are used, scores based on the opinion of hospital market insiders. We contribute to the current debate by using a subjective reputation score resorting to patient perceptions and examine its impact on the choice of hospital of patients undergoing a coronary artery bypass graft (CABG) in Germany. Our results show that 76% of the patients value hospital reputation positively when choosing a hospital. Moreover, we find evidence for a trade-off between hospital reputation and travel time, i.e. a significant share of patients is willing to accept additional travel time to get a treatment in a hospital with better reputation. The average marginal effect for hospital reputation confirms this finding, since the magnitude of the effect strengthens for higher thresholds of travel time. The results are robust for different degrees of co-morbidities and admission status.

JEL Classification: C25, D12, I11

Keywords: Hospital choice; hospital reputation; mixed logit model

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1 Adam Pilny, RWI, RGS Econ and Ruhr-Universität Bochum; Roman Mennicken, Landschaftsverband Rheinland. *– We express our appreciation to Thomas K. Bauer, Sandra Schaffner and Ansgar Wübker for helpful comments. We thank Klaus Focke, Uwe Mehlhorn and Daniel Viehweg from the BKK Federal Association. Furthermore, we thank Rüdiger Budde and Corinna Hentschker for support with the geocoding of our data. The administrative data of §21 KHEntgG was used as part of a cooperation agreement from April, 1st 2011 between the RWI and the BKK Federal Association. Financial support by the Ruhr Graduate School in Economics is gratefully acknowledged.* *– All correspondence to: Adam Pilny, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: adam.pilny@rwi-essen.de*

1 Introduction

In the health economic literature the determinants of patients' choice of hospital gained more importance over the last years (see e.g. Varkevisser et al. 2012; Wang et al. 2011; Pope 2009; Dranove and Sfekas 2008; Howard 2005). The main driving factor that intensified the appearance of studies examining the decision-making process of patients is the increasing availability and significance of quality information in the hospital sector. The majority of recent empirical studies on this topic uses objective quality indicators, such as quality report cards, to investigate the effect of quality information on the choice of hospital, ignoring a stream of literature showing that such objective quality information is often poorly understood by patients.

As Harris and Buntin (2008) point out, some quality information appears to confuse patients rather than to inform them. Hence, the use of quality information is limited due to their lack of comprehensibility. Obviously, the level of comprehension can vary among patients (Jewett and Hibbard, 1996) and the way quality information is presented affects patients' comprehension of it. The way quality reports are generally presented is criticized by many researchers (see e.g. Friedemann et al. 2009; Rothberg et al. 2008; Schauffler and Mordavsky 2001; Marshall et al. 2000; Hibbard et al. 1997). If quality information is difficult to understand, patients may dismiss it as unimportant.[1]

Hence, the design of quality reports appears to be a crucial criterion for the utilization of quality information for the patients' choice of hospital (Fasolo et al., 2010). The comprehensibility of quality information can be improved by reducing cognitive requirements, such as simple presentation or simple readability, and by highlighting important information. In addition to purely quantitative measures, qualitative ratings (e.g. good vs. bad) can improve the comprehensibility of quality information (Wasem and Geraedts, 2011).[2]

Besides objective quality measures, subjective measures, sometimes called "soft factors", are more easily understood by patients (Petersen et al., 2007). Patients reveal more interest in factors like communication with the doctor and the nursing staff, responsiveness to patient needs and cleanness of the hospital room (Sofaer et al., 2005). Vladeck et al. (1988) argue that the choice of a hospital is mainly driven by the preferences of patients, tradition and convenience. In a recent survey about the German health care system, participants were asked about their perception of hospital quality. About 86% of all patients surveyed reveal interest in such information. Furthermore, the survey revealed that patients value the competence of a hospital, the staff's qualification, the use of modern medical procedures as well as the cleanness and interior of the rooms (Geraetds, 2006).

[1] To resolve the poor comprehensibility of some quality reports, it has been recommended that patients should be involved in the selection of quality indicators (Hibbard and Jewett 1997; Lansky 1998).

[2] The design of report cards is also discussed in literature, examining ways to facilitate the presentation of complex information about health care for patients, see e.g. Vaiana and McGlynn (2002).

Publicly available quality information might increase competition by setting incentives for hospitals to invest in better quality (Hibbard et al. 2003; Barr et al. 2006). Good quality is reflected in reputation, which can be used to set itself apart from the competitors in the market. In countries with regulated prices for in-patient treatments, such as Germany, quality can be utilized by hospitals to get a competitive advantage. However, it is important to understand whether and to what extent patients consider hospital reputation in their hospital choice, i.e. responsiveness to quality information is a prerequisite for promoting competition about quality of care. Nevertheless, hospital reputation *per se* may also be affected by word-of-mouth recommendations about the perceived quality of a hospital.

We contribute to the growing literature analyzing responsiveness of patients to hospital reputation. In this context, the question arises to what extent patients accept additional travel times for a treatment in a hospital with better reputation. In our econometric analysis we explicitly model a potential trade-off between hospital reputation and travel time. With this paper, we are the first who present empirical evidence of the influence of hospital reputation on the choice of hospital in Germany by using individual data. For our analysis, we use data of patients undergoing a coronary artery bypass graft (CABG), i.e. patients seeking an elective treatment. To avoid the above mentioned potential pitfalls of objective quality indicators, we utilize an easily understood measure of hospital reputation: A subjective indicator that represents patient satisfaction with the hospital stay. Since 2005, one of the major health insurance companies in Germany conducts surveys about satisfaction of patients with their hospital stay and publishes the results on its website. This indicator is based on the perception of patients concerning the quality of their own treatment results and the amenities of the hospital. We regard this indicator of patient satisfaction as an all-encompassing and superior measure of quality itself, word-of-mouth recommendations as well as the perception of patients. Furthermore, we use the full in-patient population of patients undergoing a CABG in Germany for the year 2007.

The paper is organized as follows: Section 2 presents recent empirical evidence of quality information on the choice of hospital. An overview of the data and descriptive statistics will be provided in Section 3. A discrete choice model which bases upon the patient's decision-making process will be established in Section 4, followed by the results in Section 5. Section 6 concludes.

2 Literature

There are numerous publications examining the influence of quality information on the choice of hospital by patients. The majority of these studies identifies positive effects of such quality information on hospital choice (see e.g. Varkevisser et al. 2012; Wang et al. 2011; Pope 2009; Goldman and Romley 2008; Howard 2005; Tay 2003). Hence, patients choose more often hospitals with a better level of quality. However, the identified effects of hospital quality are different in magnitude. Thus, disparity in results may be attributed to different model designs and data sources.

A distinction of studies based on the aggregation level of the data seems indicated, as availability and characterization of data restraints the flexibility of the underlying empirical models. Studies using aggregated data on hospital-level often refer to market shares as dependent variable when examining the effect of hospital quality. E.g. Bundorf et al. (2009), Wübker et al. (2010) and Mukamel and Mushlin (1998) examine the effect of quality information and report cards on markets shares and case figures by using aggregated data. More recent studies use individual-level data to estimate the hospital choice by patients, while the hospital choice is represented via discrete choice models. This discrete choice setting allows for a more flexible model specification, e.g. in modeling the decision-making process with an underlying utility function for individuals. The majority of these studies relies predominantly on a mixed logit model with random parameters to represent the decision-making process. Due to its high popularity, the mixed logit model can be regarded as the standard approach in modeling the choice of hospital (see Varkevisser et al. 2012; Wang et al. 2011; Epstein 2010; Pope 2009; Goldman and Romley 2008; Howard 2005; Tay 2003).

Almost all studies use administrative data or individual claims of health insurers. The majority of authors chooses patients who undergo heart procedures, e.g. CABG (Wang et al. 2011; Epstein 2010), percutaneous coronary intervention (Varkevisser et al., 2012) or patients with an acute myocardial infarction (Tay, 2003). Occasionally, patients with other main diagnoses are used like pneumonia patients (Goldman and Romley, 2008) or registrants for kidney transplantations (Howard, 2005).

Considering all published articles in this field, the extent and the diversity of available quality indicators becomes apparent. In almost all cases, authors use objective measures for quality: Wang et al. (2011) and Epstein (2010) use CABG report cards providing mortality rates on hospital- and surgeon-level. Pope (2009) uses an objective ranking system underlying on hospital data that has been published in a popular magazine. Howard (2005) uses the difference between the expected and the actual graft failure rates at one-year post-transplant as a measure for quality. In her study, Tay (2003) presents hospital quality by using variables including both input and output measures of a hospital, such as the number of nurses per bed, the range of specialized services offered as well as one-year mortality and one-year complication rates of patients admitted to the hospitals.

In two studies subjective measures are used: To reflect hospital reputation Varkevisser et al. (2012) use two objective and two subjective indicators, i.e. data on readmission rates after treatment for heart failure and point prevalences of pressure ulcers as well as data on overall and specialty-specific hospital reputation scores, including one measure for cardiology. Both scores for hospital reputation have been obtained through a survey of hospital market insiders, such as practitioners, nurses and hospital management. Goldman and Romley (2008) examine the influence of hospital amenities on the choice of hospital. To display the volume of hospital amenities, they use data from a marketing survey with households asked regarding their perceptions towards hospital amenities.

Except Varkevisser et al. (2012) using data for the Netherlands, all other studies analyze the influence of quality information by using data from the US. Benchmarking of these studies is limited, because model specifications and assumptions are made conditional on available data and on regulatory restraints in hospital markets in each region or country. Thus, e.g. the definition of the choice sets for patients, the consideration of heterogeneity of patient characteristics as well as the definition of travel time differs.[3]

3 Data

3.1 Administrative DRG data

We use administrative data from the German system of diagnosis related groups (DRG) of about 19 million hospital cases treated in 1,717 hospitals for the year 2007, which is originally collected for billing purposes towards health insurance companies. It comprises all in-patient cases except psychiatric ones and includes a range of detailed information on patient characteristics such as age, gender, length of stay with admission and discharge date and status, the main diagnosis, and secondary diagnoses given the respective ICD-10-GM codes. Furthermore, the data comprise information on hospital level like ownership type (public, private not-for-profit and private for-profit), bed capacity and university hospital status. Additionally, the exact address for each hospital and the ZIP-code of the patient's residential area are available. Due to data protection, the exact address of the patient is unavailable, so that we use the centroids of the respective ZIP-codes as the residential area of a patient. All addresses of hospitals and the centroids of the ZIP codes were geo-coded. This is an identical approach to Hentschker and Mennicken (2014) for calculating travel times from patients' residences to all hospitals in the choice set.[4] By using driving time by car, we are able take geographic and infrastructural differences into account. In comparison to using the straight distance, driving time does not overestimate access in regions

[3]Some authors use straight-line distance between the residence of patients to a hospital (e.g. Goldman and Romley 2008; Howard 2005), or the actual travel time taking infrastructure into account (Varkevisser et al., 2012). Other studies do not provide further information on the definition of travel time.

[4]Like Hentschker and Mennicken (2014) we have to assume that all patients in a particular ZIP code live at the geographic centroid and patient ZIP codes were based on the home address. Geographic centroids correspond with the geographic center of each ZIP code area. The roughly 8,200 five-digit ZIP codes in Germany have an average size (median size) of 43 (27) square kilometers with a minimum of 0.14 and a maximum of 888 square kilometers. 90% of German ZIP codes are not larger than 97 square kilometers. Hence, while travel times in urban areas (with smaller ZIP code areas) are reasonable well approximated, inaccuracy increases in more rural areas.

with less comprehensive infrastructure.

3.2 Patient satisfaction index

One of the major German health insurance companies, the *Techniker Krankenkasse*, provides user-friendly and suitable-for-patient information about patient perceptions of hospital performance (Techniker Krankenkasse, 2010a). For this purpose a survey was conducted among its own insurees about "Satisfaction with the hospital treatment" asking about subjective experiences with the last hospital stay (Techniker Krankenkasse, 2010b).[5] The questionnaires are sent to patients after a hospital stay with a return envelope to minimize the risk of manipulation. The survey is conducted completely anonymously. In 2006, all contacted patients received a reminder letter after one week.[6] To ensure representative results, some inclusion criteria have to be met: Patients treated in all German hospitals were eligible. However, patients older than 80 years, in need of long-term care or with a length of stay of less than three days were excluded. The questionnaire was sent to a random sample of the remaining patients irrespective of age, gender, co-morbidities and severity of illness. For each hospital between 150 and 1,000 patients were asked to participate in the survey. Results were only published when at least 60 completed questionnaires for each hospital were available. Returned questionnaires were evaluated by using a valuation scheme. The scheme allocates points in a range between 0 and 12 to each question and concentrates all questions to 5 topics that cover different fields of satisfaction.[7] For the year 2006, data for the patient satisfaction index for the main topic "General satisfaction with the hospital" for a total of 576 hospitals is available.

3.3 Sample restrictions

In order to estimate the choice of hospital accurately, we have to ensure that the patient has a factual choice. Hence, we have to focus on patients who suffer from diseases that militate in favor of an elective hospital treatment. We follow Wang et al. (2011) and Epstein (2010) by focusing on patients undergoing a CABG. To ensure the accuracy of the sample, we compile a

[5] In 2006, the health insurance company conducted a pilot project to ascertain patient satisfaction across patients who were treated in hospitals of a particular hospital chain. A representative comparison of hospitals was able due to the high rate of return of filled questionnaires and of its good quality of data. Because of the success of the pilot project a more comprehensive project started in the second half-year in 2006, where insurees were asked about their hospital stay, when being treated in a hospital in the second half-year in 2005 or in the first half-year in 2006, respectively. Nowadays, the survey is conducted annually or biyearly. For 2006, we have no information on the number of participants. However, in 2010 in total 364,096 patients were eligible in the survey, in which 222,884 (61.2%) patients answered and returned their questionnaire.

[6] The questionnaire was developed and validated by two external institutes to ensure a user-friendly and easy understandable structure of the questions. In total, the questionnaire covers 41 questions referring to different topics.

[7] The five topics cover "General satisfaction with the hospital", "Satisfaction with the treatment result", "Satisfaction with the medical provision and care provision", "Satisfaction with the information and the communication in the hospital" and "Satisfaction with the organization and the accommodation in the hospital".

set of inclusion and exclusion criteria[8]: According to the *German Inpatient Quality Indicators* by Mansky et al. (2011), we exclude patients with another operation on the heart and those with a myocardial infarction. More than 98% of the remaining patients have either an angina pectoris (ICD-10 code: I20) or an ischemic heart disease (ICD-10 code: I25) as their main diagnosis. To ensure a consistent patient population in our final sample, we exclude patients having other main diagnoses not directly related to heart diseases (e.g. cancer). During this exclusion, we lose a total of 16 hospitals all of which treated only one patient with a CABG in 2007. Hence, the loss of the hospitals seems unproblematic as we could assume that these hospitals do not treat CABG patients regularly, so the excluded hospitals would not be comprised in the potential choice set of CABG patients. In the next step, patients with missing or false zip codes are excluded. Furthermore, we do not include patients who were transferred to other hospitals or from other hospitals, because their hospitalizations are not representing their actual hospital choice. Finally, we lose 20 hospitals and the respective patients treated in those hospitals due to missing data of the patient satisfaction index.

Porell and Adams (1995) stress the importance of an adequate method for identifying the choice set of hospital alternatives. Due to the fact, that it is *a priori* unknown which hospitals are regarded as feasible alternatives by the patients, the algorithm of determining the choice set deserves particular attention. First, we only include hospitals in our choice set that offer treatments for patients undergoing a CABG, i.e. 106 hospitals are potentially eligible. After applying the above mentioned inclusion and exclusion criteria for patients, only 63 hospitals remain in the choice set.[9] Second, we only consider hospitals as alternatives, if they are accessible within a reasonable travel time. We restrict the maximal travel time from the residence of a patient to all feasible hospital alternatives to 120 minutes. Hence, we do not consider extremely high travel times for potential hospital alternatives, since we assume that patients with travel times higher than 120 minutes do not travel from their actual residence, but instead from another origin such as a holiday stay.[10] It is reasonable to assume that patients will not necessarily choose a hospital farther away, due to the adjacency to the family and other relatives during their hospital stay. Patients expecting longer periods of hospitalization would prefer proximity to their social networks, i.e. family and friends (Wang et al., 2011). Additional travel time would raise the cost of social support networks. The actual costs for travel time from the residence of a patient to a hospital will be not represented accurately for such patients. Therefore, the inclusion of these patients can lead to biased estimation results (Varkevisser et al., 2012).

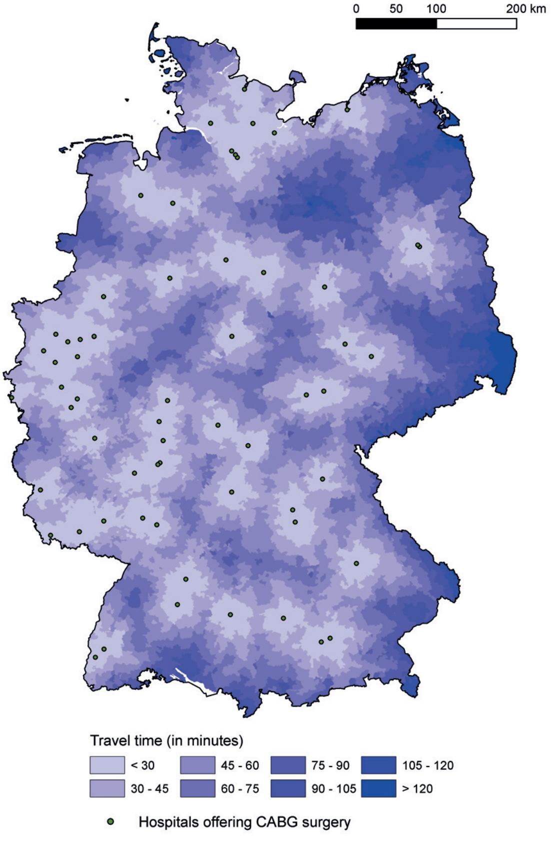
To examine a trade-off between hospital reputation and travel time, we modify the data with

[8]The exact algorithm with all inclusion and exclusion criteria displaying the corresponding number of drop outs is given in Figure A1 in the Appendix.

[9]Theoretical 83 hospitals would remain that offer CABG. Due to the fact that 20 hospitals drop out because of missing data for the patient satisfaction index, we can construct the choice set only out of the remaining 63 hospitals.

[10]The travel time restriction seems appropriate due to the fact that the majority of patients (98%) does not choose a hospital farther away than 120 minutes. A histogram of the distribution of actual travel time is presented in Figure A2 in the Appendix.

Figure 1: Accessibility of hospitals offering CABG surgery



Source: Own illustration.

respect to different thresholds of maximal travel time. The lowest threshold is restricted to 30 minutes of travel time. Further thresholds are increased successively by 15-minute steps up to 120 minutes of travel time. Figure 1 shows the accessibility of the 63 hospitals offering CABG surgery in our sample. The map shows travel time from all ZIP code centroids to the closest hospital by classifying travel time according to our thresholds. Especially in West Germany and around Hamburg hospitals are clustered. The hospital density in former GDR states is significantly lower, resulting in higher travel times for patients living in Mecklenburg-Western Pomerania and in Saxony-Anhalt. In West Germany there are also regions with higher travel times, but not in such a magnitude as in East Germany. Our sample consists of 13,409 patients treated in 63 hospitals. The sample size is composed of the number of patients times the number of hospital alternatives in their choice sets.[11]

To control for patient heterogeneity and to check the robustness of our estimates, we split the data into subsamples according to patient characteristics. Thus, we differentiate patients with respect to the severity of co-morbidities. Patients with lower severity may sort to health care providers with better quality, due to better access to publicly available information (Wang et al., 2011). For this purpose, we use the Charlson Co-morbidity Index (CCI) (Charlson et al., 1987). The CCI is a standard approach for risk adjustment and accounts for the number and severity of secondary diagnoses.[12] We classify patients into high severity, if they have at least one secondary diagnosis included in the CCI. For the mentioned samples a distinction by admission status is made. A patient has either a scheduled admission ordered by a practitioner, or is admitted as an emergency. To avoid potential biases by admission status, we also analyze two different subsamples: First, we consider the full sample comprising both types of admission status and second, we re-estimate all models only looking at patients with a scheduled admission, who are not restricted in their choice set.[13]

Descriptive statistics for the full sample are displayed in Table 1. On average, each patient has 12 hospital alternatives in his choice set. The mean travel time is 35 minutes to the actual chosen hospital. About 33% of all patients have a low severity of co-morbidities with a CCI equal to zero. The remaining 67% of patients exhibit a high severity of co-morbidities. A majority of 86% of patients has the status of a scheduled admission, whereas 14% of patients are classified as emergencies. The hospital reputation score is, on average, 79.7%.[14] 67% of all hospitals in

[11]The sample consists of 13,409 patients with an average of 11.820 alternatives in their respective choice sets. Hence, the total number of observations is 13,409$\times$11.820$\approx$158,494.

[12]For building the CCI we use diagnosis codes by Quan et al. (2005). They mapped the original ICD-9-codes into codes corresponding to the ICD-10 system.

[13]Using administrative data, we do not know the admission way of emergency cases, i.e. either as a self-referral by showing up in the emergency department or by being admitted through an ambulance. In the former case, patients induce a hospitalization by making a conscious decision probably considering travel time more than hospital reputation, while in the latter case, the ambulance crew chooses a hospital for the patient. It is reasonable to assume that the ambulance crew has better information about quality of CABG treatments in hospitals. Hence, they may choose an adequate hospital to ensure a good treatment for the patient, given the ambulance crew has the choice between several hospitals.

[14]The data for hospital reputation provide sufficient variation. A histogram of the distribution of hospital

Table 1: Descriptive statistics

	Mean	St. D.	Min.	Max.
Patient characteristics (n = 13,409)				
Travel time[a]	35.325	(25.280)	0	120
Scheduled admission	0.856	(0.351)	0	1
Emergency	0.144	(0.351)	0	1
CCI = 0	0.325	(0.468)	0	1
CCI ≥ 1	0.675	(0.468)	0	1
Number of alternatives	11.820	(5.398)	2	29
Hospital characteristics (n = 63)				
Hospital reputation	0.797	(0.056)	0.628	0.933
Public	0.667	(0.475)	0	1
Private not-for-profit	0.143	(0.353)	0	1
Private for-profit	0.190	(0.396)	0	1
Beds	976.540	(539.690)	127	3,095
University hospital	0.460	(0.502)	0	1

Notes: [a]Travel time in minutes to the actual chosen hospital. CCI = Charlson Co-morbidity Index.

the sample have a public owner, whereas hospitals in private not-for-profit and private for-profit ownership exhibit lower shares with 14% and 19%, respectively. Descriptive statistics for the samples with lower thresholds of travel time are provided in Table A2 in the Appendix. The share of scheduled admissions increases and, vice versa, the number of emergencies decreases for increasing thresholds of travel time. This is not surprising, since an ambulance crew may prefer nearby hospitals in the case of an emergency transport. Furthermore, the number of hospital alternatives in the choice sets of patients is steadily increasing for higher thresholds.

4 Model

To illustrate the decision-making process of a representative patient, we refer to the random utility theory. The utility of patient i from choosing hospital alternative $j \in \mathcal{J}$ is specified as

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{1}$$

with the deterministic component V_{ij} and the stochastic component ϵ_{ij}. The deterministic term of the utility function can be expressed as

$$V_{ij} = \beta' x_{ij}. \tag{2}$$

reputation is shown in Figure A3 in the Appendix.

It includes alternative-specific covariates x_{ij} that vary over alternatives and the corresponding coefficient vector β. The error term of the utility function ϵ_{ij} is assumed to be iid extreme value. The alternative-specific covariates x_{ij} comprise characteristics that are associated with the hospital alternative j. Patient i is confronted with a choice set $\mathcal{J}$ of potential hospitals. According to the utility function in Equation (1), patient i chooses the alternative $j \in \mathcal{J}$ that provides him the highest utility level, compared to the utility levels provided by the other alternatives that are comprised in the choice set. Thus, the probability that patient i chooses hospital j is specified as

$$\begin{aligned} p_{ij} &= Pr[U_{ij} \geq U_{ik}] \\ &= Pr[V_{ij} + \epsilon_{ij} \geq V_{ik} + \epsilon_{ik}] \\ &= Pr[\epsilon_{ik} - \epsilon_{ij} \leq V_{ij} - V_{ik}] \quad \forall k \neq j \end{aligned} \tag{3}$$

with $j, k \in \mathcal{J}$.

It is appropriate to specify the patient's choice of hospital as a mixed logit model, also referred to as random parameters logit model, with a random parameter vector β_i which contains coefficients that vary among patients, representing different tastes by patients. In contrast, the conditional logit model assumes the coefficient vector to be fixed, which implies homogeneous tastes by patients towards hospital characteristics. In order to cope with heterogeneity in patient preferences, we use the mixed logit model. Hence, the random coefficient vector $\beta_i = \beta + \mu_i$ is decomposable into a fixed component β and a random component μ_i. The random component μ_i captures the heterogeneity in the tastes of patients. Consequently, each patient has individual coefficients representing preferences towards the covariates in the model.

The variable of interest is hospital reputation. Due to the fact that the actual hospital reputation is not directly measurable, we have to use a proxy variable that has to be highly correlated with hospital reputation. For this reason, we use the continuous index of patient satisfaction to proxy for hospital reputation. It is appropriate to assume that hospital reputation is correlated with an index that represents perceptions of patients towards hospitalization. To control for costs that arise by traveling to a more distant hospital, the specification of our regression model includes travel time in minutes from the residence of the patients to each hospital alternative. Both variables, hospital reputation and travel time, are exogenous.[15]

Furthermore, we include the hospital's number of beds to control for hospital size and dummy variables for the ownership type of the hospital and university hospital status. For almost all coefficients, we assume an independent normal distribution, i.e. the coefficients being random, except for the bed variable. We assume that the coefficient for the bed variable is fixed over all patients. This allows for a higher probability of visiting a larger hospital than of visiting a

[15]Hospital reputation is exogenous, because it is included with a lag of one year. Theoretically, travel time could be endogenous if patients base their choice of residency on their preferred hospital location. However, this assumption seems unreasonable, so we assess travel time as exogenous.

smaller hospital, all else equal. We do not include alternative-invariant patient characteristics in our model. For including patient characteristics a normalization is needed, i.e. intercepts for hospital alternatives and interactions of patient-specific variables with each hospital alternative in the choice set.[16] The interpretation of such patient-specific variables is not practicable, due to the absence of a natural base category in our case. Because of the high number of alternatives in the choice set, the interpretation of all patient-specific coefficients would not make much sense. Furthermore, computational burden would arise due to a high number of additional covariates. For this reasons, we exclude patient characteristics in our model. Instead, we distinguish between differences in patient characteristics by analyzing several subsamples controlling for patient heterogeneity.

The probability of patient i choosing hospital j conditional on β_i is defined as

$$L_{ij}(\beta_i) = \frac{exp(x'_{ij}\beta_i)}{\sum_{l=1}^{m} exp(x'_{il}\beta_i)}. \tag{4}$$

In comparison with the conditional logit, the mixed logit has the limitation of not being able to condition on the coefficient vector. The mixed logit probability is therefore an unconditional choice probability, that is defined as an integral of $L_{ij}(\beta_i)$ over all possible values of β_i:

$$p_{ij} = Pr[y_i = j] = \int \left(\frac{exp(x'_{ij}\beta)}{\sum_{l=1}^{m} exp(x'_{il}\beta)} \right) f(\beta) \mathrm{d}\beta \tag{5}$$

for $j \in \mathcal{J}$. In the mixed logit model, probabilities are defined as integrals of standard logit probabilities over the density of parameters (Train, 2009). The probability is a weighted average over different values of β, in which weights are given by the density $f(\beta)$. The parameters of interest are the mean and the covariance of the density $f(\beta)$. Hence, we do not obtain estimates for the coefficient vector β_i, because the choice probabilities of the mixed logit do not depend on the parameters β_i. Finally, the parameters will be integrated out. The model is estimated via Maximum Simulated Likelihood (MSL), with simulating the likelihood function by using Halton draws. To ensure a high accuracy of the results we use 100 Halton draws for our estimations.[17]

The estimation results allow us to calculate the share of the distribution of the random parameters that is above and below zero (Train, 2009). Hence, when presenting our results we calculate the share of patients who value hospital reputation either positively or negatively. The share is derived from the cumulative standard normal distribution function. Furthermore, we calculate the average marginal effect (AME) of a 1% increase in hospital reputation. In particular, we perform simulations to calculate own marginal effects, i.e. the effect of a 1% increase in hospital

[16] An example of the econometric modeling is provided by Cameron and Trivedi (2009) on page 509.

[17] For the estimation we use the user-written Stata command `mixlogit` by Hole (2007). The accuracy of the estimated results can be increased with the number of Halton draws. However, an increase in the number of Halton draws comes along with additional computing time. The choice of 100 Halton draws yields similar results to the choice of 1,000 Halton draws (Train, 2009). Hence, our choice of 100 Halton draws can be regarded as reasonable.

reputation of hospital alternative j on the choice probability of hospital alternative j, all else equal. Thus, we neglect cross marginal effects, i.e. those effects of changes in hospital reputation of other hospital alternatives on the choice probability of hospital alternative j. The AME is the average over all own marginal effects of all hospital alternatives. However, calculating the standard errors of the marginal effects for a mixed logit model is associated with computational restraints. Hence, we only calculate the mean of the AME for assessing the quantitative effect of an increase in hospital reputation.

The choice of hospital can be illustrated as a trade-off between hospital reputation and travel time to the hospital. In general, an interaction term of both concerned variables would capture this trade-off. However, an interaction term comes along with problems of interpretation. Ai and Norton (2003) show that an interaction term in non-linear models does not allow for correct inference about sign, magnitude or statistical significance of the estimated interaction effect. Instead of using an interaction term, we choose another way to illustrate the trade-off between hospital reputation and travel time: We estimate the model for several samples with different thresholds of maximal travel time. When patients accept additional travel time for a treatment in a hospital with better reputation, the share of coefficients that is above zero as well as the magnitude of the AME with respect to the predicted likelihood of choosing a hospital should increase for higher thresholds of travel time.

The mixed logit has the advantage that limitations of the conditional logit do not occur. In particular, the conditional logit assumes homogenous error variances that lead to the independence of irrelevant alternatives (IIA) assumption. The IIA is a quite restrictive assumption in the context of hospital choice, since it assumes that the ratio of choice probabilities between two hospitals is not affected by the existence of a third hospital alternative. In fact, a patient has to consider all hospital alternatives in his choice set. Thus, it is likely that the choice of a hospital is influenced by other eligible hospitals, i.e. the IIA assumption is not tenable in hospital choice models.[18] The application of a mixed logit model allows us to avoid the problem of the IIA assumption. In comparison to the conditional logit model, the mixed logit model allows for arbitrary correlation over alternatives in the stochastic component of the utility function (Revelt and Train, 1998). By decomposing the coefficient vector β_i into β and μ_i, the utility function can be rewritten as $U_{ij} = \beta' x_{ij} + \mu_i' x_{ij} + \epsilon_{ij}$. Hence, the stochastic component is augmented by the term $\mu_i' x_{ij}$, which allows for correlation over alternatives. A second disadvantage of the conditional logit can also be captured by the mixed logit. As long as individual tastes of patients vary over observed variables they can be captured by the conditional logit model, but in the appearance of unobserved taste variation the iid assumption will be violated. Even if unobserved heterogeneity in tastes of patients exists, the mixed logit model provides unbiased estimates.

[18] The problem of potentially biased estimates due to the restrictive IIA assumption in the context of hospital choice is discussed in Porell and Adams (1995). Also recent studies like Epstein (2010), Wang et al. (2011) or Varkevisser et al. (2012) mention the disadvantages that come along with IIA in standard logit approaches.

5 Results

Estimation results for the coefficients of hospital reputation, obtained by the MSL estimator, are presented in Table 2. For all model specifications a Wald χ^2 test for joint significance of the estimated standard deviations has been applied. The null hypothesis that all estimated standard deviations of the coefficients are equal to zero can be rejected.[19] This shows the superiority of the mixed logit model over the conditional logit model, since the mixed logit framework allows for heterogeneous preferences of patients towards hospital characteristics that, in our case, obviously exist.

First, we consider the results for the sample with the travel time restriction of 120 minutes that are shown in the bottom panel of Table 2. The positive sign of the estimated mean of the coefficient for hospital reputation indicates that a higher reputation score increases the probability of choosing a hospital. The estimated standard deviation for the coefficient of hospital reputation is also highly significant. Hence, there is considerable heterogeneity in tastes towards hospital reputation among patients. In the full sample, about 76% of all patients undergoing a CABG value hospital reputation positively for their choice of a hospital.[20] By excluding emergency cases from the sample, the share of patients with a scheduled admission having a positive valuation increases slightly. For emergency cases, the share of patients with a positive valuation (67%) is somewhat lower than in the full sample covering both types of admission status.

The results for the samples with thresholds of travel time reveal a trade-off between hospital reputation and travel time. For the sample with a travel time restriction of 30 minutes, the estimations of the mean are either weak statistically significant or not significant at all. Surprisingly, the mean for emergencies with a maximal travel time of 30 minutes is significantly negative. However, in the samples covering both types of admission and in the samples covering only scheduled admissions, for increasing thresholds of maximal travel time the estimated means of the coefficient for hospital reputation are throughout highly significant with positive sign and increase steadily in their magnitude. Furthermore, the estimations for the standard deviations are also statistically significant. 52% of patients exhibit a positive valuation of hospital reputation for a threshold of 30 minutes of travel time. This share increases steadily up to 76% for a threshold of 120 minutes. A similar picture is given for the samples with scheduled admissions and emergencies. Thus, when the radius of eligible hospitals increases, a higher fraction of patients takes into account hospital reputation positively in its decision-making process. Accordingly, we can state that a significant fraction of patients accepting additional travel time is more sensitive to hospital reputation. Hence, these patients are willing to choose hospitals

[19]Wald χ^2 statistics for all model specifications can be obtained from Tables A3 to A16 in the Appendix.

[20]The share of the distribution that is above zero is derived from a table of the standard normal cumulative distribution function. It is calculated as $P(\beta > 0) = Prob(z > \Phi(-b/s))$ with mean b and standard deviation s of the distribution of coefficients for hospital reputation. Thus, $P(\beta > 0) = Prob(z > \Phi(19.078/27.405)) = Prob(z > \Phi(-0.696)) = 1 - Prob(z < \Phi(-0.696)) = 1 - 0.242 = 0.758$. Hence, 76% of all patients have a positive coefficient with respect to the distribution.

Table 2: Mixed logit coefficients for *Hospital Reputation*

	Full sample		Only scheduled		Only emergencies	
Travel time threshold	Mean	S. E.	Mean	S. E.	Mean	S. E.
30 minutes						
Mean	1.443	(1.770)	4.427*	(1.906)	−9.348*	(3.969)
St. D.	26.717***	(4.895)	22.572***	(4.597)	27.590***	(7.585)
Share of positive β	*51.99%*		*57.93%*		*36.69%*	
45 minutes						
Mean	6.839***	(1.278)	8.455***	(1.451)	0.575	(2.899)
St. D.	39.343***	(3.174)	41.040***	(3.654)	35.805***	(6.007)
Share of positive β	*56.75%*		*58.32%*		*50.80%*	
60 minutes						
Mean	9.753***	(0.952)	10.852***	(1.050)	5.391*	(2.115)
St. D.	35.365***	(1.915)	37.030***	(2.070)	28.118***	(3.954)
Share of positive β	*61.03%*		*61.41%*		*57.53%*	
75 minutes						
Mean	11.923***	(0.815)	13.423***	(0.924)	5.303**	(1.749)
St. D.	27.881***	(1.445)	30.287***	(1.603)	19.985***	(3.438)
Share of positive β	*66.64%*		*67.00%*		*60.64%*	
90 minutes						
Mean	14.388***	(0.768)	15.839***	(0.861)	5.469***	(1.593)
St. D.	27.132***	(1.252)	28.683***	(1.385)	17.196***	(3.050)
Share of positive β	*70.19%*		*70.88%*		*62.55%*	
105 minutes						
Mean	17.297***	(0.773)	19.111***	(0.884)	6.635***	(1.551)
St. D.	27.285***	(1.133)	29.385***	(1.275)	17.804***	(2.797)
Share of positive β	*73.57%*		*74.22%*		*64.43%*	
120 minutes						
Mean	19.078***	(0.833)	20.870***	(0.885)	7.269***	(1.592)
St. D.	27.405***	(1.183)	28.954***	(1.198)	17.099***	(3.142)
Share of positive β	*75.80%*		*76.42%*		*66.64%*	

Notes: Robust standard errors in parentheses. All model specifications include further control variables that are not displayed in this table. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Mixed logit coefficients for *Hospital Reputation* for different degrees of co-morbidities

	Low severity[a]				**High severity**[b]			
	With emergencies		Without emergencies		With emergencies		Without emergencies	
Travel time threshold	Mean	S. E.	Mean	S. E.	Mean	S. E.	Mean	S. E.
30 minutes								
Mean	2.154	(6.016)	0.630	(21.681)	2.027	(1.714)	4.685*	(2.003)
St. D.	94.103***	(17.030)	66.634	(275.630)	18.059***	(3.451)	18.560***	(4.556)
Share of positive β	*50.80%*		-		*54.38%*		*59.87%*	
45 minutes								
Mean	15.911***	(3.307)	17.556***	(4.028)	4.777***	(1.310)	6.160***	(1.451)
St. D.	68.354***	(6.897)	70.202***	(8.818)	31.209***	(3.116)	32.662***	(3.232)
Share of positive β	*59.10%*		*59.87%*		*55.96%*		*57.53%*	
60 minutes								
Mean	13.370***	(1.989)	14.132***	(2.312)	8.190***	(1.042)	9.602***	(1.175)
St. D.	42.677***	(3.836)	42.317***	(4.417)	32.105***	(2.078)	35.065***	(2.339)
Share of positive β	*62.17%*		*62.93%*		*60.26%*		*60.64%*	
75 minutes								
Mean	17.153***	(1.912)	19.329***	(2.272)	9.988***	(0.882)	11.471***	(0.993)
St. D.	34.200***	(3.101)	36.111***	(3.509)	26.069***	(1.579)	28.677***	(1.791)
Share of positive β	*69.15%*		*70.54%*		*64.80%*		*65.54%*	
90 minutes								
Mean	20.520***	(1.865)	21.940***	(2.044)	12.098***	(0.817)	13.661***	(0.936)
St. D.	33.034***	(2.865)	33.525***	(3.065)	24.857***	(1.343)	27.014***	(1.550)
Share of positive β	*73.24%*		*74.22%*		*68.79%*		*69.50%*	
105 minutes								
Mean	25.078***	(2.038)	28.912***	(2.348)	14.972***	(0.835)	16.328***	(0.934)
St. D.	33.574***	(2.671)	37.018***	(2.936)	25.941***	(1.283)	27.058***	(1.415)
Share of positive β	*77.34%*		*78.23%*		*71.90%*		*72.57%*	
120 minutes								
Mean	28.563***	(2.363)	33.040***	(2.676)	15.926***	(0.839)	17.470***	(0.915)
St. D.	34.540***	(2.855)	39.002***	(3.098)	24.834***	(1.187)	26.572***	(1.298)
Share of positive β	*79.67%*		*80.23%*		*73.89%*		*74.54%*	

Notes: Robust standard errors in parentheses. All model specifications include further control variables that are not displayed in this table. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a]Patients with CCI = 0. [b]Patients with CCI $\geq$ 1. CCI = Charlson Co-morbidity Index.

farther away, to undergo a CABG surgery.

The mean of the coefficient for travel time is negative for all samples in Table 2, i.e. the likelihood of choosing a hospital decreases with distance. Almost all patients (96%-99%) value travel time negatively. University hospitals and private not-for-profit hospitals are less often chosen in comparison to public hospitals.

To analyze the effect of hospital reputation with respect to heterogeneity in patient characteristics, we estimate the model for the subsamples differentiating between the degrees of co-morbidities. Estimation results and the corresponding shares of patients with a positive valuation of hospital reputation are presented in Table 3. Considering the results for the sample with the travel time restriction of 120 minutes at the bottom panel of the table, a significant share of 80% of all patients without co-morbidities of the CCI exhibits a positive valuation, while 74% of patients with co-morbidities of the CCI have a positive valuation. In analyzing the trade-off between hospital reputation and travel time, the same pattern is revealed as mentioned before. Except of the threshold of 30 minutes, the share of patients with a positive valuation increases steadily for higher thresholds. On average, the share of coefficients that is above zero is higher in the sample of patients without co-morbidities.

For all samples, the share of patients with a positive valuation of hospital reputation increases marginally by excluding emergency cases. Hence, we cannot state that emergency cases have on average other preferences towards hospital reputation compared to patients with scheduled admission, all else equal. Initially, we would have expected an insignificant mean for emergency cases. A plausible explanation of this result can be different ways of being admitted as an emergency, i.e. either by an ambulance or as a self-referral by showing up in the emergency department of a hospital. Significant standard deviations of hospital reputation for emergencies indicate heterogeneity in tastes among emergency cases. As we are not able to assign the share of patients who are sensitive to hospital reputation to those patients hospitalized via self-referral, we think that the results may partly be explained by this unobservable heterogeneity in emergency cases.

The results show that hospital reputation has a significant influence on the choice of a hospital in qualitative terms. As shown in Table 4, the average marginal effect for a 1% increase in hospital reputation is 0.0018 in the 30 minutes sample. The AME has to be interpreted with respect to the probability of choosing a hospital in the particular sample. In the sample with the 30 minutes threshold a patient has, on average, 3 hospital alternatives in his choice set. Thus, the predicted probability of choosing a hospital $\hat{y}$ is 0.3378. An increase in hospital reputation of 1% would increase the likelihood of choosing a hospital by 0.0018, all else equal. To assess whether the magnitude of this AME is small or large, the relative change in percent with respect to $\hat{y}$ is calculated. In this case, the relative change in $\hat{y}$ is 0.54% (0.0018/0.3378), indicating a quite small marginal effect. Because the choice sets of patients differ in samples with different

Table 4: Average marginal effects for *Hospital Reputation*

Travel time threshold	Full sample	Only scheduled	Only emergencies
30 Minutes			
Average marginal effect	0.0018	0.0022	-0.0021
Relative change, in %	*0.54%*	*0.64%*	*-0.69%*
45 Minutes			
Average marginal effect	0.0037	0.0043	0.0018
Relative change, in %	*1.48%*	*1.67%*	*0.77%*
60 Minutes			
Average marginal effect	0.0035	0.0038	0.0021
Relative change, in %	*1.78%*	*1.92%*	*1.11%*
75 Minutes			
Average marginal effect	0.0033	0.0038	0.0013
Relative change, in %	*2.04%*	*2.32%*	*0.88%*
90 Minutes			
Average marginal effect	0.0033	0.0038	0.0010
Relative change, in %	*2.54%*	*2.91%*	*0.82%*
105 Minutes			
Average marginal effect	0.0033	0.0038	0.0011
Relative change, in %	*3.15%*	*3.58%*	*1.09%*
120 Minutes			
Average marginal effect	0.0030	0.0034	0.0010
Relative change, in %	*3.55%*	*4.04%*	*1.24%*

Notes: The relative change in % shows the magnitude of the marginal effect w.r.t. the predicted probability of choosing a hospital.

Table 5: Average marginal effects for *Hospital Reputation* for different degrees of co-morbidities

	Low severity[a]		**High severity**[b]	
Travel time threshold	With emergencies	Without emergencies	With emergencies	Without emergencies
30 Minutes				
Average marginal effect	0.0066	0.0028	0.0015	0.0022
Relative change, in %	*1.98%*	*0.81%*	*0.44%*	*0.63%*
45 Minutes				
Average marginal effect	0.0067	0.0072	0.0026	0.0031
Relative change, in %	*2.60%*	*2.76%*	*1.06%*	*1.24%*
60 Minutes				
Average marginal effect	0.0046	0.0050	0.0030	0.0034
Relative change, in %	*2.26%*	*2.43%*	*1.55%*	*1.71%*
75 Minutes				
Average marginal effect	0.0043	0.0051	0.0028	0.0035
Relative change, in %	*2.58%*	*3.05%*	*1.78%*	*2.21%*
90 Minutes				
Average marginal effect	0.0044	0.0049	0.0029	0.0033
Relative change, in %	*3.35%*	*3.70%*	*2.30%*	*2.56%*
105 Minutes				
Average marginal effect	0.0042	0.0047	0.0030	0.0033
Relative change, in %	*4.02%*	*4.48%*	*2.85%*	*3.12%*
120 Minutes				
Average marginal effect	0.0040	0.0045	0.0027	0.0030
Relative change, in %	*4.68%*	*5.28%*	*3.17%*	*3.58%*

Notes: The relative change in % shows the magnitude of the marginal effect w.r.t. the predicted probability of choosing a hospital.
[a]Patients with CCI = 0. [b]Patients with CCI $\geq$ 1. CCI = Charlson Co-morbidity Index.

thresholds of maximal travel time, also the predicted probabilities for choosing a hospital are different. While $\hat{y}$ is 0.3378 in the 30 minutes sample, $\hat{y}$ decreases to 0.0864 in the 120 minutes sample, because each patient faces more hospital alternatives. Therefore, the AMEs are not comparable with each other over the samples. Rather, they have to be interpreted for each sample with respect to the corresponding $\hat{y}$. Even though the AME itself does not increase for higher travel times, the relative change in $\hat{y}$ does. Hence, the relative impact of a 1% increase in hospital reputation increases for higher travel time thresholds, i.e. it increases from 0.54% in the 30 minutes sample to 3.55% in the 120 minutes sample. The relative effects are even stronger by excluding emergency cases. Emergency cases exhibit somewhat weak effects. The same pattern is observable in Table 5 for different degrees of co-morbidities. This finding confirms the hypothesis that patients with a lower degree of co-morbidities prefer providers with better performance (Wang et al., 2011). Due to computational restraints, we are not able to calculate the standard errors of the AME. Therefore, we are restricted in making statements about the statistical significance of the marginal effects. Nevertheless, the AMEs are significant in economic terms, since the findings show that patients accepting higher travel times are more sensitive to changes in hospital reputation.

5.1 Robustness check

To examine the trade-off between hospital reputation and travel time, we successively increase the sample size by a truncation of maximal travel time for different thresholds. By augmenting the sample for a higher threshold, we have to consider that the samples change in two ways. First, we add patients with a higher travel time to their actual chosen hospital. Second, those patients who were included in the sample with the former threshold will exhibit new choice sets, because we increase the radius of accessibility.[21] Our results show that the fraction of patients with a positive valuation of hospital reputation increases by setting up higher thresholds for travel time. The question is, if this increase in the share of positive coefficients for hospital reputation can actually be attributed to the added patients with a higher travel time or if a part is driven by those patients with lower travel time thresholds who face new choice sets.

To confirm our findings mentioned above, we test the robustness of our results by the following approach: For each setting up of the threshold, we only include those patients with higher travel time and keep the choice sets of the former patients unchanged. E.g. by increasing the threshold from 30 minutes up to 45 minutes, we hold the patients with a maximal travel time of 30 minutes and their respective choice sets unchanged as in the 30 minutes sample. Then, we add all patients with a travel time between 30–45 minutes to their actual chosen hospital. This procedure is applied for all thresholds.[22] After this modification of all samples, the mixed logit

[21]By setting up the threshold, patients that are included in the former sample will exhibit new choice sets comprising hospitals alternatives farther away.

[22]Because 30 minutes are the lowest threshold, the modification of samples is applied only for all thresholds

model is estimated.[23] Compared to the results above, the estimated coefficients for the mean of hospital reputation are somewhat higher and the shares of patients with a positive valuation of travel time are slightly lower. In total, the results of this robustness check are quite similar to the original results. Hence, we can state that the increase in the share of positive coefficients for hospital reputation is widely driven by patients who accept additional travel time. The change of choice sets of patients that were already included in samples with lower thresholds of travel time has no significant influence on the increase of the share of coefficients that are above zero. The AMEs for hospital reputation are also calculated for the modified samples in the robustness check. The finding of an increasing relative impact for higher travel times can be confirmed.[24]

6 Conclusion

In this study, we have examined the influence of hospital reputation on the hospital choice of patients undergoing a CABG using a mixed logit model that takes a trade-off between hospital reputation and travel time into account. Hence, the associated costs that arise by choosing a more distant hospital are considered. We are the first who use subjective patient perceptions, displayed in a publicly available patient satisfaction index, as a proxy for hospital reputation. Previous studies used either objective quality indicators based on quantitative figures, or if subjective reputation scores were used, such scores based on the opinion of hospital market insiders (see e.g. Varkevisser et al. 2012; Pope 2009).

The results show that hospital reputation has a significant impact on the choice of a hospital and that a fraction of 76% of all patients exhibits a positive valuation on hospital reputation. In general, our results are in line with other studies even though 76% of patients valuing hospital reputation positively are less than around 90% as in Varkevisser et al. (2012) or Wang et al. (2011). This disparity may be attributed to the fact, that they examine the impact of quality itself, rather than the impact of hospital reputation. Furthermore, institutional differences between the countries may explain the difference in the shares, since the authors examine the choice behavior in the Netherland and the US, respectively. The access to quality or reputation data can differ as well as the sensitivity towards such information and its utilization by patients.

Another key finding is the evidence for a trade-off between hospital reputation and travel time. Our results reveal that the share of patients valuing hospital reputation positively increases steadily for increasing thresholds of travel time. This finding is confirmed by the average marginal effect of hospital reputation. The magnitude of the effect of a 1% increase in hospital reputation increases steadily for higher travel times. This means that the fraction of patients who accept

between 45–120 minutes.

[23]The estimation results and the share of positive coefficients for hospital reputation only are shown in Tables A17 and A18 in the Appendix.

[24]The AMEs from the robustness check are provided in Tables A19 and A20 in the Appendix.

additional travel time is more sensitive to hospital reputation. Our results are robust for different degrees of co-morbidities and admission status. Separate analyses according to disease severity and admission status do not change the results substantially. Even emergency cases reveal a valuation for hospitals with better reputation, which might be due to a conscious decision by the patient or by a better informed ambulance crew.

However, the analysis comes along with some limitations. In our data, we cannot differentiate the patients according to socioeconomic attributes. Furthermore, it was not possible to include patient characteristics in our model that control for observable patient heterogeneity as discussed in Section 4. Furthermore, we have no information considering the practitioners, who are responsible for the hospital admission of the patient.

The economic relevance of reputation in the hospital market is considerable. Our results indicate that a large share of patients is aware of hospital reputation and considers it, when making a choice. Even though it is questionable if objective quality indicators are actually used by patients, there is no doubt that the majority of patients banks on hospital reputation. However, a hospital can use its reputation as an advantage to set itself apart from its competitors, especially in Germany, where competition on prices does not occur due to a standardized reimbursement system with DRGs.

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7 Appendix

Table A1: Definition of variables

Variable	Definition
Hospital reputation	Continuous patient satisfaction index, ranging from 0 to 1
Travel time	Travel time from the residence of a patient to a hospital in minutes
Public	1, if public hospital, 0 otherwise
Private not-for-profit	1, if private not-for-profit hospital, 0 otherwise
Private for-profit	1, if private for-profit hospital, 0 otherwise
Beds	Number of beds in a hospital
University hospital	1, if university hospital, 0 otherwise
Scheduled admission	1, if scheduled admission by the doctor, 0 otherwise
Emergency	1, if admission as emergency, 0 otherwise
CCI = 0	1, if Charlson Comorbidity Index = 0, 0 otherwise
CCI $\geq$ 1	1, if Charlson Comorbidity Index $\geq$ 1, 0 otherwise
Number of alternatives	Number of hospital alternatives in the choice set

Figure A1: Inclusion and exclusion criteria for patients with CABG

Potential patients with CABG
n = 63,308 patients, 106 hospitals

↓

Exclusion because patient has another operation on his heart:
- 15,744 patients get excluded
- 2 hospitals get excluded

↓

Exclusion because patient has a myocardial infarction:
- 8,995 patients get excluded
- 3 hospitals get excluded

↓

Exclusion because patient has not the main diagnosis angina pectoris (ICD-10 code: I20) or ischemic heart disease (ICD-10 code: I25):
- 684 patients get excluded
- 16 hospitals get excluded

↓

Exclusion due to missing or false coded zip code:
- 561 patients get excluded
- 1 hospital gets excluded

↓

Exclusion because transfer to other hospital:
- 10,645 patients get excluded
- 0 hospitals get excluded

↓

Exclusion because transfer from other hospital:
- 7,398 patients get excluded
- 1 hospital gets excluded

↓

Exclusion due to missing data on patient satisfaction in the treating hospital:
- 5,457 patients get excluded
- 20 hospitals get excluded

↓

Exclusion due to travel time restriction of 120 minutes:
- 415 patients get excluded
- 0 hospitals get excluded

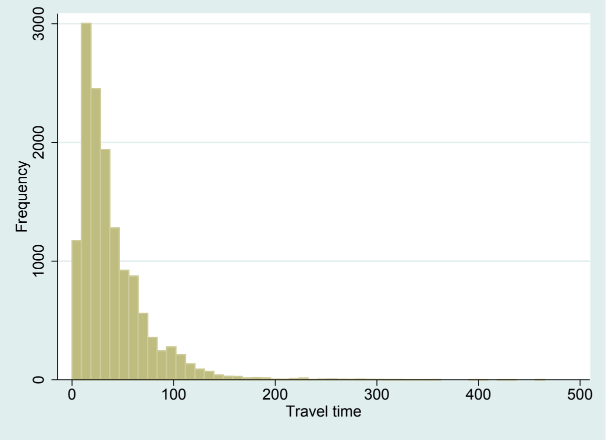
↓

Patients with CABG (full sample)
n = 158,494 (13,409 patients, 63 hospitals)

↓

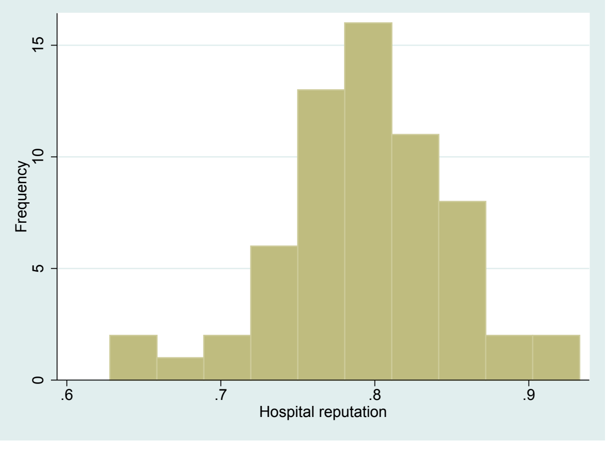
Patients with CABG (only scheduled)
n = 135,235 (11,475 patients, 63 hospitals)

Figure A2: Histrogram of the distribution of travel time (in minutes)



Source: Own illustration.

Figure A3: Histrogram of the distribution of hospital reputation



Source: Own illustration.

Table A2: Descriptive statistics for travel time thresholds

Travel time threshold	Mean	St. D.	Min.	Max.
30 minutes (n = 3,487)				
Travel time[a]	16.366	(6.823)	0	30
Scheduled admission	0.813	(0.390)	0	1
Emergency	0.187	(0.390)	0	1
CCI = 0	0.327	(0.469)	0	1
CCI $\geq$ 1	0.673	(0.469)	0	1
Number of alternatives	2.961	(1.238)	2	9
45 minutes (n = 6,705)				
Travel time[a]	20.682	(10.051)	0	45
Scheduled admission	0.829	(0.377)	0	1
Emergency	0.171	(0.377)	0	1
CCI = 0	0.315	(0.465)	0	1
CCI $\geq$ 1	0.685	(0.465)	0	1
Number of alternatives	3.987	(2.400)	2	12
60 minutes (n = 9,404)				
Travel time[a]	24.673	(13.660)	0	60
Scheduled admission	0.837	(0.370)	0	1
Emergency	0.163	(0.370)	0	1
CCI = 0	0.314	(0.464)	0	1
CCI $\geq$ 1	0.686	(0.464)	0	1
Number of alternatives	5.087	(3.349)	2	14
75 minutes (n = 11,545)				
Travel time[a]	28.316	(17.077)	0	75
Scheduled admission	0.845	(0.362)	0	1
Emergency	0.155	(0.362)	0	1
CCI = 0	0.321	(0.467)	0	1
CCI $\geq$ 1	0.679	(0.467)	0	1
Number of alternatives	6.254	(3.845)	2	15
90 minutes (n = 12,534)				
Travel time[a]	31.220	(19.972)	0	90
Scheduled admission	0.850	(0.357)	0	1
Emergency	0.150	(0.357)	0	1
CCI = 0	0.322	(0.467)	0	1
CCI $\geq$ 1	0.678	(0.467)	0	1
Number of alternatives	7.733	(4.174)	2	19
105 minutes (n = 13,102)				
Travel time[a]	33.628	(22.892)	0	105
Scheduled admission	0.854	(0.354)	0	1
Emergency	0.146	(0.354)	0	1
CCI = 0	0.322	(0.467)	0	1
CCI $\geq$ 1	0.678	(0.467)	0	1
Number of alternatives	9.524	(4.700)	2	23

Notes: [a]Travel time in minutes to the actual chosen hospital. CCI = Charlson Co-morbidity Index.

Table A3: Mixed logit coefficients – 30 minutes restriction

	Full sample		Only scheduled		Only emergencies	
	Mean	S. E.	Mean	S. E.	Mean	S. E.
Mean						
Hospital reputation	1.443	(1.770)	4.427^{*}	(1.906)	-9.348^{*}	(3.969)
Travel time	-0.313^{***}	(0.025)	-0.316^{***}	(0.027)	-0.285^{***}	(0.034)
Private not-for-profit	-1.904^{***}	(0.504)	-2.451^{***}	(0.616)	-1.282^{*}	(0.618)
Private for-profit	0.003	(0.155)	0.571^{**}	(0.176)	-1.889^{***}	(0.312)
University hospital	-0.592^{***}	(0.128)	-0.555^{***}	(0.153)	-1.102^{***}	(0.293)
Beds$\times 10^{-2}$	-0.044^{**}	(0.014)	-0.021	(0.016)	-0.091^{*}	(0.041)
St. D.						
Hospital reputation	26.717^{***}	(4.895)	22.572^{***}	(4.597)	27.590^{***}	(7.585)
Travel time	0.168^{***}	(0.027)	0.178^{***}	(0.027)	0.067	(0.047)
Private not-for-profit	6.557^{***}	(1.132)	8.207^{***}	(1.344)	3.729^{**}	(1.409)
Private for-profit	0.041	(0.027)	0.026	(0.044)	0.009	(0.038)
University hospital	0.090	(0.291)	0.840	(0.458)	0.001	(0.042)
Observations	10,324		8,212		2,112	
Patients	3,487		2,835		652	
Hospitals	49		49		47	
Wald χ^2	204.41^{***}		150.78^{***}		107.08^{***}	
Log-Likelihood	$-2,396.950$		$-1,941.740$		-429.171	

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4: Mixed logit coefficients – 45 minutes restriction

	Full sample		Only scheduled		Only emergencies	
	Mean	S. E.	Mean	S. E.	Mean	S. E.
Mean						
Hospital reputation	6.839^{***}	(1.278)	8.455^{***}	(1.451)	0.575	(2.899)
Travel time	-0.274^{***}	(0.013)	-0.275^{***}	(0.015)	-0.273^{***}	(0.021)
Private not-for-profit	-1.281^{***}	(0.191)	-1.281^{***}	(0.218)	-1.474^{***}	(0.331)
Private for-profit	-0.260^{*}	(0.119)	0.038	(0.132)	-1.630^{***}	(0.272)
University hospital	-0.610^{***}	(0.089)	-0.477^{***}	(0.097)	-1.483^{***}	(0.233)
Beds$\times 10^{-2}$	-0.003	(0.011)	0.012	(0.012)	-0.037	(0.024)
St. D.						
Hospital reputation	39.343^{***}	(3.174)	41.040^{***}	(3.654)	35.805^{***}	(6.007)
Travel time	0.137^{***}	(0.012)	0.145^{***}	(0.014)	0.091^{***}	(0.020)
Private not-for-profit	2.184^{***}	(0.401)	2.275^{***}	(0.441)	1.288	(0.758)
Private for-profit	0.010	(0.051)	0.011	(0.089)	0.047	(0.049)
University hospital	0.138	(0.151)	0.204	(0.222)	0.040	(0.117)
Observations	26,733		21,771		4,962	
Patients	6,705		5,558		1,147	
Hospitals	62		61		60	
Wald χ^2	502.86^{***}		358.44^{***}		208.21^{***}	
Log-Likelihood	$-4,792.513$		$-4,042.699$		-708.951	

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5: Mixed logit coefficients – 60 minutes restriction

	Full sample		Only scheduled		Only emergencies	
	Mean	S. E.	Mean	S. E.	Mean	S. E.
Mean						
Hospital reputation	9.753***	(0.952)	10.852***	(1.050)	5.391*	(2.115)
Travel time	−0.215***	(0.008)	−0.210***	(0.010)	−0.236***	(0.019)
Private not-for-profit	−0.736***	(0.120)	−0.634***	(0.138)	−1.450***	(0.289)
Private for-profit	−0.042	(0.085)	0.211*	(0.094)	−1.156***	(0.213)
University hospital	−0.276***	(0.064)	−0.109	(0.069)	−1.289***	(0.184)
Beds$\times 10^{-2}$	0.025**	(0.008)	0.042***	(0.009)	−0.016	(0.019)
St. D.						
Hospital reputation	35.365***	(1.915)	37.030***	(2.070)	28.118***	(3.954)
Travel time	0.092***	(0.007)	0.091***	(0.008)	0.081***	(0.019)
Private not-for-profit	1.104***	(0.273)	1.077**	(0.353)	1.209*	(0.609)
Private for-profit	0.002	(0.057)	0.011	(0.079)	0.033	(0.041)
University hospital	0.598*	(0.273)	0.603	(0.371)	0.098	(0.138)
Observations	47,836		39,571		8,265	
Patients	9,404		7,868		1,536	
Hospitals	63		63		62	
Wald χ^2	671.06***		474.98***		187.42***	
Log-Likelihood	$-7,057.680$		$-6,041.583$		$-1,000.405$	

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A6: Mixed logit coefficients – 75 minutes restriction

	Full sample		Only scheduled		Only emergencies	
	Mean	S. E.	Mean	S. E.	Mean	S. E.
Mean						
Hospital reputation	11.923***	(0.815)	13.423***	(0.924)	5.303**	(1.749)
Travel time	−0.192***	(0.006)	−0.188***	(0.007)	−0.225***	(0.015)
Private not-for-profit	−0.497***	(0.103)	−0.377***	(0.110)	−1.239***	(0.264)
Private for-profit	0.424***	(0.074)	0.643***	(0.083)	−0.690***	(0.180)
University hospital	−0.163**	(0.054)	−0.025	(0.058)	−0.888***	(0.149)
Beds$\times 10^{-2}$	0.045***	(0.007)	0.064***	(0.008)	−0.029	(0.017)
St. D.						
Hospital reputation	27.881***	(1.445)	30.287***	(1.603)	19.985***	(3.438)
Travel time	0.083***	(0.005)	0.083***	(0.005)	0.096***	(0.011)
Private not-for-profit	1.430***	(0.195)	1.325***	(0.223)	2.028***	(0.416)
Private for-profit	0.024	(0.074)	0.053	(0.120)	0.028	(0.049)
University hospital	1.053***	(0.196)	1.051***	(0.222)	0.154	(0.482)
Observations	72,223		60,255		11,968	
Patients	11,549		9,752		1,797	
Hospitals	63		63		63	
Wald χ^2	$1,027.79^{***}$		774.58^{***}		231.25^{***}	
Log-Likelihood	$-9,189.607$		$-7,900.893$		$-1,214.683$	

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A7: Mixed logit coefficients – 90 minutes restriction

	Full sample		Only scheduled		Only emergencies	
	Mean	S. E.	Mean	S. E.	Mean	S. E.
Mean						
Hospital reputation	14.388***	(0.768)	15.839***	(0.861)	5.469***	(1.593)
Travel time	−0.181***	(0.005)	−0.172***	(0.005)	−0.209***	(0.012)
Private not-for-profit	−0.616***	(0.094)	−0.479***	(0.098)	−1.194***	(0.244)
Private for-profit	0.649***	(0.068)	0.844***	(0.074)	−0.514**	(0.164)
University hospital	−0.169***	(0.050)	−0.030	(0.052)	−0.793***	(0.137)
Beds$\times 10^{-2}$	0.053***	(0.007)	0.071***	(0.007)	−0.029*	(0.015)
St. D.						
Hospital reputation	27.132***	(1.252)	28.683***	(1.385)	17.196***	(3.050)
Travel time	0.075***	(0.003)	0.071***	(0.004)	0.084***	(0.008)
Private not-for-profit	1.683***	(0.152)	1.496***	(0.174)	2.152***	(0.343)
Private for-profit	0.163	(0.120)	0.083	(0.236)	0.047	(0.064)
University hospital	1.248***	(0.145)	1.030***	(0.184)	0.374	(0.515)
Observations	96,921		81,620		15,301	
Patients	12,534		10,646		1,888	
Hospitals	63		63		63	
Wald χ^2	$1,362.61^{***}$		$1,193.93^{***}$		309.49^{***}	
Log-Likelihood	$-10,578.313$		$-9,174.846$		$-1,322.354$	

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A8: Mixed logit coefficients – 105 minutes restriction

	Full sample		Only scheduled		Only emergencies	
	Mean	S. E.	Mean	S. E.	Mean	S. E.
Mean						
Hospital reputation	17.297***	(0.773)	19.111***	(0.884)	6.635***	(1.551)
Travel time	−0.179***	(0.005)	−0.174***	(0.005)	−0.208***	(0.012)
Private not-for-profit	−0.881***	(0.095)	−0.793***	(0.107)	−1.178***	(0.234)
Private for-profit	0.835***	(0.067)	1.043***	(0.082)	−0.460**	(0.160)
University hospital	−0.216***	(0.049)	−0.093	(0.052)	−0.823***	(0.134)
Beds$\times 10^{-2}$	0.056***	(0.006)	0.075***	(0.007)	−0.025	(0.014)
St. D.						
Hospital reputation	27.285***	(1.133)	29.385***	(1.275)	17.804***	(2.797)
Travel time	0.083***	(0.003)	0.082***	(0.004)	0.086***	(0.007)
Private not-for-profit	1.797***	(0.153)	1.710***	(0.202)	2.001***	(0.367)
Private for-profit	0.457	(0.467)	0.729	(0.513)	0.002	(0.072)
University hospital	1.161***	(0.174)	1.024***	(0.276)	0.582	(0.433)
Observations	124,783		105,800		18,983	
Patients	13,102		11,176		1,926	
Hospitals	63		63		63	
Wald χ^2	1,639.91***		1,186.05***		328.44***	
Log-Likelihood	−12,091.594		−10,551.579		−1,424.461	

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A9: Mixed logit coefficients – 120 minutes restriction

	Full sample		Only scheduled		Only emergencies	
	Mean	S. E.	Mean	S. E.	Mean	S. E.
Mean						
Hospital reputation	19.078***	(0.833)	20.870***	(0.885)	7.269***	(1.592)
Travel time	−0.175***	(0.005)	−0.169***	(0.005)	−0.199***	(0.010)
Private not-for-profit	−1.052***	(0.101)	−0.921***	(0.105)	−1.355***	(0.261)
Private for-profit	0.934***	(0.078)	1.108***	(0.079)	−0.414**	(0.156)
University hospital	−0.215***	(0.047)	−0.085	(0.048)	−0.799***	(0.131)
Beds$\times 10^{-2}$	0.050***	(0.006)	0.067***	(0.007)	−0.029*	(0.014)
St. D.						
Hospital reputation	27.405***	(1.183)	28.954***	(1.198)	17.099***	(3.142)
Travel time	0.084***	(0.003)	0.082***	(0.003)	0.081***	(0.006)
Private not-for-profit	1.849***	(0.173)	1.637***	(0.187)	2.271***	(0.459)
Private for-profit	1.268***	(0.357)	1.726***	(0.246)	0.109	(0.103)
University hospital	1.020***	(0.249)	0.749**	(0.248)	0.269	(0.325)
Observations	158,494		135,235		23,259	
Patients	13,409		11,475		1,934	
Hospitals	63		63		63	
Wald χ^2	1,450.51***		1,394.15***		377.74***	
Log-Likelihood	−13,218.142		−11,597.178		−1,467.198	

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A10: Mixed logit coefficients for different degrees of co-morbidities – 30 minutes restriction

	Low severity[a]		**High severity**[b]	
	With emergencies	Without emergencies	With emergencies	Without emergencies
Mean				
Hospital reputation	2.154	0.630	2.027	4.685*
	(6.016)	(21.681)	(1.714)	(2.003)
Travel time	−0.358***	−0.366	−0.293***	−0.301***
	(0.074)	(0.216)	(0.023)	(0.027)
Private not-for-profit	−1.181*	−1.344	−1.836***	−1.884**
	(0.585)	(8.896)	(0.452)	(0.586)
Private for-profit	−2.132***	−0.773	0.379*	0.887***
	(0.422)	(6.790)	(0.166)	(0.204)
University hospital	−1.637***	−1.107	−0.344*	−0.267
	(0.366)	(1.142)	(0.140)	(0.167)
Beds$\times 10^{-2}$	−0.032	−0.044	−0.032*	−0.008
	(0.032)	(0.061)	(0.016)	(0.018)
St. D.				
Hospital reputation	94.103***	66.634	18.059***	18.560***
	(17.030)	(275.630)	(3.451)	(4.556)
Travel time	0.192*	0.221**	0.140***	0.150***
	(0.090)	(0.073)	(0.023)	(0.026)
Private not-for-profit	0.497	7.564	4.964***	5.413***
	(1.891)	(47.796)	(0.722)	(1.055)
Private for-profit	0.065	0.021	0.003	0.078
	(0.122)	(0.617)	(0.031)	(0.058)
University hospital	0.256	0.879	0.381	0.811
	(0.591)	(2.225)	(0.349)	(0.455)
Observations	3,413	2,704	6,911	5,508
Patients	1,140	924	2,347	1,911
Hospitals	47	47	49	49
Wald χ^2	38.90***	34.59***	178.89***	134.61***
Log-Likelihood	-789.550	-653.011	-1,570.988	-1,270.298

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a]Patients with CCI = 0. [b]Patients with CCI ≥ 1. CCI = Charlson Co-morbidity Index.

Table A11: Mixed logit coefficients for different degrees of co-morbidities – 45 minutes restriction

	Low severity[a]		**High severity**[b]	
	With emergencies	Without emergencies	With emergencies	Without emergencies
Mean				
Hospital reputation	15.911***	17.556***	4.777***	6.160***
	(3.307)	(4.028)	(1.310)	(1.451)
Travel time	−0.311***	−0.315***	−0.260***	−0.252***
	(0.027)	(0.035)	(0.014)	(0.015)
Private not-for-profit	−1.586***	−1.517***	−1.239***	−1.183***
	(0.300)	(0.341)	(0.211)	(0.244)
Private for-profit	−1.238***	−0.797**	0.093	0.318*
	(0.222)	(0.248)	(0.126)	(0.140)
University hospital	−1.330***	−1.132***	−0.366***	−0.254*
	(0.193)	(0.217)	(0.097)	(0.105)
Beds$\times 10^{-2}$	0.013	0.035	−0.007	0.008
	(0.019)	(0.023)	(0.012)	(0.013)
St. D.				
Hospital reputation	68.354***	70.202***	31.209***	32.662***
	(6.897)	(8.818)	(3.116)	(3.232)
Travel time	0.160***	0.172***	0.127***	0.126***
	(0.026)	(0.035)	(0.014)	(0.015)
Private not-for-profit	0.430	0.218	2.147***	2.103***
	(0.525)	(0.494)	(0.318)	(0.386)
Private for-profit	0.019	0.144	0.054	0.039
	(0.164)	(0.216)	(0.061)	(0.086)
University hospital	0.180	0.233	0.252	0.059
	(0.181)	(0.171)	(0.323)	(0.206)
Observations	8,206	6,704	18,527	15,067
Patients	2,115	1,744	4,590	3,814
Hospitals	61	61	61	60
Wald χ^2	160.26***	94.77***	347.40***	305.28***
Log-Likelihood	-1,505.267	-1,268.685	-3,244.072	-2,750.604

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a]Patients with CCI = 0. [b]Patients with CCI ≥ 1. CCI = Charlson Co-morbidity Index.

Table A12: Mixed logit coefficients for different degrees of co-morbidities – 60 minutes restriction

	Low severity[a]		**High severity**[b]	
	With emergencies	Without emergencies	With emergencies	Without emergencies
Mean				
Hospital reputation	13.370***	14.132***	8.190***	9.602***
	(1.989)	(2.312)	(1.042)	(1.175)
Travel time	−0.222***	−0.218***	−0.209***	−0.203***
	(0.015)	(0.020)	(0.010)	(0.010)
Private not-for-profit	−0.486**	−0.327	−0.854***	−0.748***
	(0.182)	(0.208)	(0.145)	(0.173)
Private for-profit	−0.489**	−0.116	0.186	0.366***
	(0.155)	(0.174)	(0.098)	(0.110)
University hospital	−0.554***	−0.329**	−0.114	0.010
	(0.118)	(0.127)	(0.075)	(0.081)
Beds$\times 10^{-2}$	0.040**	0.059***	0.017	0.033**
	(0.014)	(0.017)	(0.009)	(0.011)
St. D.				
Hospital reputation	42.677***	42.317***	32.105***	35.065***
	(3.836)	(4.417)	(2.078)	(2.339)
Travel time	0.096***	0.099***	0.089***	0.085***
	(0.013)	(0.016)	(0.008)	(0.009)
Private not-for-profit	0.235	0.591	1.136***	0.899
	(0.699)	(0.603)	(0.288)	(0.539)
Private for-profit	0.040	0.082	0.024	0.082
	(0.082)	(0.116)	(0.063)	(0.105)
University hospital	0.490	0.688	0.535	0.444
	(0.539)	(0.641)	(0.359)	(0.356)
Observations	14,549	11,991	33,287	27,580
Patients	2,957	2,461	6,447	5,407
Hospitals	63	63	63	63
Wald χ^2	226.40***	136.86***	487.61***	407.23***
Log-Likelihood	-2,211.148	-1,891.495	-4,817.099	-4,129.172

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a]Patients with CCI = 0. [b]Patients with CCI $\geq$ 1. CCI = Charlson Co-morbidity Index.

Table A13: Mixed logit coefficients for different degrees of co-morbidities – 75 minutes restriction

	Low severity[a]		**High severity**[b]	
	With emergencies	Without emergencies	With emergencies	Without emergencies
Mean				
Hospital reputation	17.153***	19.329***	9.988***	11.471***
	(1.912)	(2.272)	(0.882)	(0.993)
Travel time	−0.208***	−0.213***	−0.186***	−0.179***
	(0.012)	(0.016)	(0.007)	(0.008)
Private not-for-profit	−0.353	−0.168	−0.573***	−0.475***
	(0.187)	(0.215)	(0.119)	(0.131)
Private for-profit	0.172	0.533**	0.545***	0.705***
	(0.145)	(0.165)	(0.085)	(0.094)
University hospital	−0.471***	−0.282*	−0.025	0.084
	(0.106)	(0.118)	(0.063)	(0.069)
Beds$\times 10^{-2}$	0.063***	0.090***	0.038***	0.055***
	(0.014)	(0.016)	(0.008)	(0.009)
St. D.				
Hospital reputation	34.200***	36.111***	26.069***	28.677***
	(3.101)	(3.509)	(1.579)	(1.791)
Travel time	0.092***	0.098***	0.079***	0.076***
	(0.008)	(0.012)	(0.005)	(0.006)
Private not-for-profit	1.539***	1.546**	1.241***	1.061***
	(0.396)	(0.471)	(0.205)	(0.297)
Private for-profit	0.028	0.227	0.029	0.004
	(0.132)	(0.224)	(0.080)	(0.124)
University hospital	1.375***	1.753***	0.910***	0.671
	(0.366)	(0.361)	(0.216)	(0.354)
Observations	22,234	18,493	49,989	41,762
Patients	3,707	3,117	7,842	6,635
Hospitals	63	63	63	63
Wald χ^2	294.67***	183.84***	798.71***	590.39***
Log-Likelihood	-2,903.456	-2,484.038	-6,249.512	-5,392.493

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a]Patients with CCI = 0. [b]Patients with CCI $\geq$ 1. CCI = Charlson Co-morbidity Index.

Table A14: Mixed logit coefficients for different degrees of co-morbidities – 90 minutes restriction

	Low severity[a]		**High severity**[b]	
	With emergencies	Without emergencies	With emergencies	Without emergencies
Mean				
Hospital reputation	20.520***	21.940***	12.098***	13.661***
	(1.865)	(2.044)	(0.817)	(0.936)
Travel time	−0.197***	−0.187***	−0.171***	−0.167***
	(0.010)	(0.011)	(0.005)	(0.006)
Private not-for-profit	−0.445*	−0.345	−0.691***	−0.570***
	(0.174)	(0.194)	(0.110)	(0.121)
Private for-profit	0.559***	0.822***	0.707***	0.888***
	(0.136)	(0.147)	(0.078)	(0.086)
University hospital	−0.437***	−0.242*	−0.033	0.060
	(0.099)	(0.102)	(0.058)	(0.063)
Beds$\times 10^{-2}$	0.069***	0.089***	0.045***	0.063***
	(0.013)	(0.015)	(0.008)	(0.008)
St. D.				
Hospital reputation	33.034***	33.525***	24.857***	27.014***
	(2.865)	(3.065)	(1.343)	(1.550)
Travel time	0.085***	0.080***	0.069***	0.067***
	(0.007)	(0.007)	(0.004)	(0.004)
Private not-for-profit	1.900***	1.827***	1.467***	1.313***
	(0.300)	(0.379)	(0.181)	(0.213)
Private for-profit	0.095	0.246	0.049	0.150
	(0.526)	(0.321)	(0.101)	(0.190)
University hospital	1.695***	1.570***	0.905***	0.878***
	(0.271)	(0.325)	(0.219)	(0.238)
Observations	30,520	25,646	66,401	55,974
Patients	4,036	3,412	8,498	7,234
Hospitals	63	63	63	63
Wald χ^2	371.71***	315.64***	1,049.21***	871.08***
Log-Likelihood	-3,384.122	-2,916.733	-7,166.167	-6,230.725

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a]Patients with CCI = 0. [b]Patients with CCI ≥ 1. CCI = Charlson Co-morbidity Index.

Table A15: Mixed logit coefficients for different degrees of co-morbidities – 105 minutes restriction

	Low severity[a]		**High severity**[b]	
	With emergencies	Without emergencies	With emergencies	Without emergencies
Mean				
Hospital reputation	25.078***	28.912***	14.972***	16.328***
	(2.038)	(2.348)	(0.835)	(0.934)
Travel time	−0.203***	−0.204***	−0.173***	−0.166***
	(0.011)	(0.012)	(0.005)	(0.005)
Private not-for-profit	−0.942***	−0.891***	−0.899***	−0.787***
	(0.195)	(0.204)	(0.110)	(0.115)
Private for-profit	0.855***	1.210***	0.879***	1.036***
	(0.142)	(0.153)	(0.078)	(0.088)
University hospital	−0.536***	−0.395***	−0.087	0.008
	(0.101)	(0.114)	(0.056)	(0.059)
Beds$\times 10^{-2}$	0.072***	0.103***	0.052***	0.067***
	(0.013)	(0.015)	(0.007)	(0.008)
St. D.				
Hospital reputation	33.574***	37.018***	25.941***	27.058***
	(2.671)	(2.936)	(1.283)	(1.415)
Travel time	0.097***	0.100***	0.079***	0.076***
	(0.007)	(0.008)	(0.003)	(0.004)
Private not-for-profit	2.564***	2.522***	1.504***	1.350***
	(0.351)	(0.314)	(0.173)	(0.195)
Private for-profit	0.796*	0.228	0.490*	0.887**
	(0.372)	(0.665)	(0.205)	(0.339)
University hospital	1.893***	2.073***	0.976***	0.780**
	(0.304)	(0.318)	(0.186)	(0.261)
Observations	40,056	33,862	84,727	71,938
Patients	4,224	3,585	8,878	7,591
Hospitals	63	63	63	63
Wald χ^2	364.07***	306.10***	1,238.87***	1,034.77***
Log-Likelihood	-3,884.072	-3,354.103	-8,158.346	-7,156.497

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a]Patients with CCI = 0. [b]Patients with CCI ≥ 1. CCI = Charlson Co-morbidity Index.

Table A16: Mixed logit coefficients for different degrees of co-morbidities – 120 minutes restriction

	Low severity[a]		High severity[b]	
	With emergencies	Without emergencies	With emergencies	Without emergencies
Mean				
Hospital reputation	28.563***	33.040***	15.926***	17.470***
	(2.363)	(2.676)	(0.839)	(0.915)
Travel time	−0.200***	−0.204***	−0.167***	−0.161***
	(0.010)	(0.012)	(0.005)	(0.005)
Private not-for-profit	−1.171***	−1.246***	−1.030***	−0.880***
	(0.228)	(0.249)	(0.113)	(0.112)
Private for-profit	1.048***	1.414***	0.953***	1.076***
	(0.163)	(0.167)	(0.079)	(0.085)
University hospital	−0.559***	−0.390***	−0.085	0.002
	(0.102)	(0.109)	(0.054)	(0.057)
Beds$\times 10^{-2}$	0.066***	0.090***	0.046***	0.062***
	(0.013)	(0.015)	(0.007)	(0.008)
St. D.				
Hospital reputation	34.540***	39.002***	24.834***	26.572***
	(2.855)	(3.098)	(1.187)	(1.298)
Travel time	0.105***	0.108***	0.077***	0.075***
	(0.007)	(0.009)	(0.004)	(0.004)
Private not-for-profit	2.603***	2.817***	1.591***	1.261***
	(0.440)	(0.392)	(0.214)	(0.211)
Private for-profit	1.635	1.504	0.727	1.375***
	(0.998)	(0.866)	(0.460)	(0.240)
University hospital	1.734***	2.022***	0.883**	0.492
	(0.395)	(0.346)	(0.285)	(0.341)
Observations	51,509	43,889	106,985	91,346
Patients	4,359	3,715	9,050	7,760
Hospitals	63	63	63	63
Wald χ^2	404.98***	301.04***	1,137.97***	1,081.17***
Log-Likelihood	-4,380.502	-3,802.929	-8,773.069	-7,740.024

Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a]Patients with CCI = 0. [b]Patients with CCI ≥ 1. CCI = Charlson Co-morbidity Index.

Table A17: Robustness check – Mixed logit coefficients for *Hospital Reputation*

	Full sample		Only scheduled		Only emergencies	
Travel time threshold	Mean	S. E.	Mean	S. E.	Mean	S. E.
45 minutes						
Mean	5.941***	(1.362)	7.280***	(1.521)	0.605	(3.014)
St. D.	36.659***	(4.350)	35.910***	(4.668)	35.860***	(8.324)
Share of positive β	*56.36%*		*57.93%*		*50.8%*	
60 minutes						
Mean	10.476***	(1.118)	12.281***	(1.318)	5.712*	(2.528)
St. D.	43.706***	(2.661)	46.727***	(3.143)	36.210***	(5.564)
Share of positive β	*59.48%*		*60.26%*		*56.36%*	
75 minutes						
Mean	13.000***	(0.937)	15.049***	(1.097)	5.064**	(1.922)
St. D.	32.773***	(1.854)	36.268***	(2.079)	22.790***	(4.029)
Share of positive β	*65.54%*		*65.91%*		*58.71%*	
90 minutes						
Mean	15.690***	(0.880)	17.663***	(1.029)	5.841***	(1.747)
St. D.	30.774***	(1.496)	33.788***	(1.790)	19.225***	(3.557)
Share of positive β	*69.50%*		*69.85%*		*61.79%*	
105 minutes						
Mean	18.172***	(0.848)	20.330***	(0.973)	6.718***	(1.668)
St. D.	29.819***	(1.325)	32.547***	(1.492)	19.313***	(3.193)
Share of positive β	*72.91%*		*73.24%*		*63.68%*	
120 minutes						
Mean	20.120***	(0.886)	21.543***	(0.958)	7.225***	(1.628)
St. D.	30.031***	(1.308)	30.758***	(1.353)	17.716***	(3.449)
Share of positive β	*74.86%*		*75.80%*		*65.91%*	

Notes: Robust standard errors in parentheses. All model specifications include further control variables that are not displayed in this table. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A18: Robustness check – Mixed logit coefficients for *Hospital Reputation* for different degrees of co-morbidities

	Low severity[a]				**High severity**[b]			
	With emergencies		Without emergencies		With emergencies		Without emergencies	
Travel time threshold	Mean	S. E.	Mean	S. E.	Mean	S. E.	Mean	S. E.
45 minutes								
Mean	16.847***	(3.891)	19.763***	(5.056)	3.804**	(1.381)	5.272***	(1.537)
St. D.	74.001***	(8.940)	82.753***	(13.905)	28.522***	(4.462)	29.919***	(4.407)
Share of positive β	*59.10%*		*59.48%*		*55.17%*		*57.14%*	
60 minutes								
Mean	16.722***	(2.707)	17.538***	(3.052)	8.458***	(1.216)	9.998***	(1.405)
St. D.	58.042***	(5.907)	59.241***	(7.178)	38.600***	(2.891)	41.452***	(3.314)
Share of positive β	*61.41%*		*61.79%*		*58.71%*		*59.48%*	
75 minutes								
Mean	19.085***	(2.313)	21.807***	(2.885)	10.710***	(0.995)	12.442***	(1.141)
St. D.	41.558***	(4.046)	45.366***	(4.926)	29.775***	(1.958)	32.815***	(2.254)
Share of positive β	*67.72%*		*68.44%*		*64.06%*		*64.80%*	
90 minutes								
Mean	22.931***	(2.243)	26.397***	(2.859)	13.236***	(0.928)	14.703***	(1.079)
St. D.	38.868***	(3.693)	42.465***	(4.287)	28.133***	(1.584)	30.588***	(1.844)
Share of positive β	*72.24%*		*73.24%*		*68.08%*		*68.44%*	
105 minutes								
Mean	26.551***	(2.178)	30.813***	(2.722)	15.423***	(0.887)	17.183***	(1.018)
St. D.	36.949***	(3.020)	41.534***	(3.913)	28.032***	(1.457)	29.846***	(1.650)
Share of positive β	*76.42%*		*77.04%*		*70.88%*		*71.90%*	
120 minutes								
Mean	31.789***	(2.480)	34.969***	(2.723)	16.359***	(0.880)	17.841***	(1.053)
St. D.	39.352***	(3.252)	43.220***	(3.804)	26.439***	(1.347)	28.494***	(1.831)
Share of positive β	*79.10%*		*79.10%*		*73.24%*		*73.57%*	

Notes: Robust standard errors in parentheses. All model specifications include further control variables that are not displayed in this table. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a]Patients with CCI = 0. [b]Patients with CCI $\geq$ 1. CCI = Charlson Co-morbidity Index.

Table A19: Robustness check – Average marginal effects for *Hospital Reputation*

Travel time threshold	Full sample	Only scheduled	Only emergencies
45 Minutes			
Average marginal effect	0.0029	0.0031	0.0019
Relative change, in %	*0.85%*	*0.91%*	*0.59%*
60 Minutes			
Average marginal effect	0.0043	0.0049	0.0028
Relative change, in %	*1.59%*	*1.78%*	*1.13%*
75 Minutes			
Average marginal effect	0.0040	0.0046	0.0017
Relative change, in %	*1.92%*	*2.16%*	*0.88%*
90 Minutes			
Average marginal effect	0.0041	0.0048	0.0014
Relative change, in %	*2.49%*	*2.88%*	*0.92%*
105 Minutes			
Average marginal effect	0.0040	0.0046	0.0013
Relative change, in %	*3.06%*	*3.53%*	*1.06%*
120 Minutes			
Average marginal effect	0.0037	0.0041	0.0012
Relative change, in %	*3.49%*	*3.88%*	*1.19%*

Notes: The relative change in % shows the magnitude of the marginal effect w.r.t. the predicted probability of choosing a hospital.

Table A20: Robustness check – Average marginal effects for *Hospital Reputation* for different degrees of co-morbidities

	Low severity[a]		**High severity**[b]	
Travel time threshold	With emergencies	Without emergencies	With emergencies	Without emergencies
45 Minutes				
Average marginal effect	0.0070	0.0089	0.0019	0.0023
Relative change, in %	*2.03%*	*2.58%*	*0.55%*	*0.67%*
60 Minutes				
Average marginal effect	0.0056	0.0058	0.0035	0.0040
Relative change, in %	*2.03%*	*2.07%*	*1.32%*	*1.46%*
75 Minutes				
Average marginal effect	0.0055	0.0061	0.0034	0.0040
Relative change, in %	*2.51%*	*2.74%*	*1.65%*	*1.89%*
90 Minutes				
Average marginal effect	0.0055	0.0066	0.0036	0.0041
Relative change, in %	*3.22%*	*3.84%*	*2.24%*	*2.52%*
105 Minutes				
Average marginal effect	0.0052	0.0059	0.0035	0.0040
Relative change, in %	*3.92%*	*4.43%*	*2.71%*	*3.07%*
120 Minutes				
Average marginal effect	0.0048	0.0054	0.0032	0.0036
Relative change, in %	*4.52%*	*5.09%*	*3.04%*	*3.36%*

Notes: The relative change in % shows the magnitude of the marginal effect w.r.t. the predicted probability of choosing a hospital.
[a]Patients with CCI = 0. [b]Patients with CCI $\geq$ 1. CCI = Charlson Co-morbidity Index.