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Subjective and objective quality reporting and choice of hospital: Evidence from maternal care services in Germany

UNIVERSITÄT DUISBURG ESSEN
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RWI

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Subjective and objective quality reporting and choice of hospital: Evidence from maternal care services in Germany

Abstract

We study patient choice of healthcare provider based on both objective and subjective quality measures in the context of maternal care hospital services in Germany. Objective measures are obtained from publicly reported clinical indicators, while subjective measures are based on satisfaction scores from a large and nationwide patient survey. We merge both quality metrics to detailed hospital discharge records and quantify the additional distance expectant mothers are willing to travel to give birth in maternity clinics with higher reported quality. Our results reveal that patients are on average willing to travel between 0.7-4.2 additional kilometers for a one standard deviation increase in reported quality. Furthermore, patients respond independently to both objective and subjective quality measures, suggesting that satisfaction scores may constitute important complements to clinical indicators when choosing healthcare provider.

JEL Classifications: C25, D82, H51, I11, I18.

Keywords: hospital competition, hospital choice, maternal care, quality reporting.

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*CINCH and University of Duisburg-Essen. Corresponding Author: CINCH — Health Economics Research Center,Weststadttürme, Berliner Platz 6–8 DE-451 27 Essen, Germany. Phone: +49 (0)201 183 6326. E-mail: daniel.avdic@uni-due.de. *We thank Matthias Bäuml and seminar participants at the RGS doctoral conference in economics in Dortmund, SMYE conference in Halle an der Saale, LAGV conferencein Aix-en-Provence, ESPE conference in Glasgow, the annual Lithuanian economics meeting in Vilnius,EEA conference in Lisbon for valuable comments. We are also grateful to Tautvydas Januškevicius and Joseph Montalbo for excellent SQL programming and research assistance. Financial support from the Federal Ministry of Education and Research (BMBF) is gratefully acknowledged.*
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1 Introduction

Since 2006, all German hospitals are by law required to report standardized quality information of the services they offer. These reports disclose the most important information for prospective patients, such as availability of medical services, clinical patient outcomes, capacity and competency of the medical staff. The aim of the legislation is twofold: to give hospitals an opportunity to advertise the range and quality of services they provide and to improve the transparency and competition in the German hospital market. As such, this regulation enhances healthcare consumers' scope of making informed choices of provider for elective treatment. In combination with a prospective reimbursement system with predetermined prices per service, the ultimate goal is to allow patients to discriminate between hospitals in terms of quality and penalize under-performing providers in the market. Crucially, the existence of such a market mechanism relies on the assumption that healthcare consumers respond and react rationally to available information about provider quality.

In this paper we empirically investigate to what extent healthcare consumers vary in their responses to provider performance depending on the nature of the quality information. Specifically, we relate the choices of maternity clinics of expectant mothers to objective (clinical indicators) and subjective (satisfaction scores) quality metrics using rich German data from administrative hospital discharge records, linked to publicly available information about provider quality. We choose to focus on maternal care in Germany for several reasons: first, healthcare consumers in Germany are entirely free to choose hospital due to the universal health insurance system, which covers treatment in all hospitals, and the absence of a gate-keeping system, which regulates access into specialized care[1]. Furthermore, the market for hospital childbirths is highly competitive with many buyers and sellers of the service[2]. Finally, consumers in this market are likely to provide effort to make substantiated choices because they value any information that allows them to scrutinize their options[3] and they have extensive time to compare their options over the course of the pregnancy. Thus, the context of German maternal care suggests a close to optimal market setting where high-stakes patients are able to make informed choices between competing providers.

Our empirical analysis entails the use of three merged datasets on hospital care and hospital quality from Germany. We first extract hospital births between 2009 and 2012

[1]See, e.g., Busse and Blümel (2014) for a review of healthcare provision in Germany.

[2]Germany has the highest density of hospital beds in Europe. See https://www.destatis.de/Europa/EN/Topic/PopulationLabourSocial/Health/HospitalBeds.html.

[3]Giving birth is an activity frequently involving a substantial amount of anxiety for the patient. For example, pregnancy-related anxiety (PrA) is a disorder which affects around 14% of all childbearing women (see, e.g., Alder *et al.*, 2007; Blackmore *et al.*, 2016).

from a rich patient-level dataset of hospital discharge records, containing a 10% representative sample of the German population. The data includes a wide range of patient characteristics, services received, clinical outcomes, and geographical locations of the hospitals and of each patient's registered home address down to the postal code level. We link this information to a set of objective quality indicators taken from standardized report cards that all hospitals are required to provide biannually. These indicators include information about complication and mortality rates for various procedures performed at the hospital, quantity and quality of the hospital staff, and provision of various supplementary medical services. Finally, we complement the objective quality indicators with subjective quality information, retrieved from a nationwide survey administrated by one of the largest public health insurance providers in Germany. The survey includes information on patients' satisfaction with their medical treatment, staffing, communication, organization, and accommodation in the hospital. One advantage of linking the discharge records directly to the quality information is that the latter corresponds to the exact information that prospective patients have access to, in contrast to information derived from the hospital data[4,5].

To implement an economically relevant measure of the willingness to pay for higher reported quality of a hospital, we use information on the distance between an individual's home and the chosen hospital. Specifically, to measure the distance-quality trade-off that patients face, we construct a measure of the willingness to travel for a given improvement in reported quality. We first estimate a simple linear probability model that a given patient choose the closest hospital as a function of its relative quality among its competitors within a predefined choice set. Subsequently, we model patient choice structurally using a random utility model framework from which we are able to compute marginal utilities and thereby provide a direct estimate of the average willingness to travel for higher reported hospital quality.

The literature on the quality-choice nexus in healthcare is relatively scarce but growing. Some studies have concluded that individuals do respond to reported quality by an increase in the likelihood of choosing a provider with better quality ratings[6]. Our

[4]While we do not claim that patients use the quality reports or the patient satisfaction survey in their search, we believe that this information is processed through various online provider search platforms, such as https://www.weisse-liste.de, which are largely based on the quality data we use in our analysis. Pross *et al.* (2017) show that prospective patients frequently use this online search portal to search for providers.

[5]For example, misreporting in the quality data would create a, potentially endogenous, discrepancy between the publicly available information and the discharge data. Using the quality reports directly avoids this problem.

[6]See, e.g., Werner *et al.* (2012); Varkevisser *et al.* (2012); Santos *et al.* (2016); Bundorf *et al.* (2009); Mukamel and Mushlin (1998); Cutler *et al.* (2004); Dranove and Sfekas (2008); Baker *et al.* (2003); Hodgkin (1996); Pope (2009); Gaynor *et al.* (2016)

results generally confirm these findings, but show in addition that patient responses vary substantially depending on the specific quality indicator. Importantly, patients respond significantly to subjective quality information also after conditioning on objective quality. This suggests that patient satisfaction scores provide a complementary, patient-valued, source of information about the quality of a hospital beyond established clinical indicators. Turning to our structural choice model, we estimate that an expectant mother is on average willing to travel an additional 0.7–4.2 kilometers (0.5–5.5 minutes travel time by car) to give birth in a hospital with a one standard deviation higher reported quality. This excess willingness to travel corresponds to up to one-third of the average distance to the closest hospital for individuals in our sample. Finally, our findings are robust to a set of sensitivity checks with respect to model specification and variable definitions.

Our contributions to the literature are several: First, we study an important context that closely resembles an optimal market setting for analyzing provider choice with respect to quality. Second, we use quality information directly observed by prospective patients which allows us to directly probe the impact of an important healthcare policy tool. Third, we are able to compare the responsiveness of two qualitatively different dimensions of quality, objective and subjective, which can be argued to correspond to different behavioral responses. These contributions could thus yield further insight into the competition-choice-quality nexus upon which many of today's healthcare systems are built around.

The paper is organized as follows. The next section relates out work to the existing literature and provides a short summary of the relevant characteristics of the German healthcare system. Section 3 discusses the different data sets we use in our empirical analysis and provides summary statistics of our sample. Section 4 describes our econometric framework. Section 5 reports the results from estimation. Section 6 concludes.

2 Background

2.1 Related Literature

The role played by quality as a factor explaining patients' choices of healthcare provider is a key component of the quality-competition theory, according to which providers have incentives to compete on quality when prices are fixed (Gaynor, 2006; Brekke *et al.*, 2014). However, hospital competition on quality is possible only if demand for healthcare is not inelastic with respect to quality. As such, flexible patient choice of provider has been introduced in many healthcare systems across the world as a way to make healthcare demand more responsive to quality (Propper, 2018). Over the last decade, several studies

have evaluated the association between quality and choice for elective care, finding that patient choice is to some extent responsive to quality (Pope, 2009; Varkevisser *et al.*, 2012; Moscone *et al.*, 2012; Santos *et al.*, 2016; Gaynor *et al.*, 2016; Moscelli *et al.*, 2016)[7]. Most previous studies have only considered clinical (objective) quality indicators. To our knowledge, only three studies (Moscone *et al.*, 2012; Pilny and Mennicken, 2014; Gutacker *et al.*, 2016) analyzed the influence of social interaction and subjective quality on patient's choice of hospital. Moreover, while a number of studies have found that distance to the hospital has a significant effect on patients' choice (Sivey, 2012; Porell and Adams, 1995), only a few have explicitly considered the trade-off between distance and quality[8] as we do in this paper.

The literature on the interaction between choice and quality in the specific context of maternal care is scant. O'Cathain *et al.* (2002) report evidence for Wales that a large minority of women giving birth did not feel like they exercised an informed choice in their maternity care. They show that evidence based leaflets were not effective in promoting informed choice in women using maternity services using a sample of 13 maternity units in Wales. Wagle *et al.* (2004) show that distance to hospital and higher socioeconomic status are the main drivers of choice of place of maternal delivery (i.e., home versus hospital) in Nepal, but the study does not include any quality measure. Related to this, there is also some evidence that differences in healthcare experience or environment at critical times can affect psychological status of the mothers during pregnancy (Jomeen and Martin, 2008).

2.2 Institutional Setting

The German healthcare system is jointly organized by federal and state level institutions and provides healthcare for all citizens and permanent residents. The German health insurance system is characterized by the coexistence of the public statutory health insurance (SHI) and the substitute private health insurance (PHI). Access to healthcare is ensured by mandatory membership in one of the over 110 SHI firms, or in one of the around 50 PHI firms, respectively[9]. The SHI covers about 90 percent of the German population[10]. Insurance under the SHI is mandatory for employees with gross wage earnings below a defined threshold (€59K/$73K annually in 2018). In the SHI family

[7]This result also holds generally for the choice of health insurance plans with higher reported ratings. See, e.g., Bünnings *et al.* (2017); Jin and Sorensen (2006); Chernew *et al.* (2008); Beaulieu (2002); Wedig and Tai-Seale (2002); Scanlon *et al.* (2002).

[8]See, e.g., Santos *et al.* (2016); Moscelli *et al.* (2016); Gutacker *et al.* (2016); Pilny and Mennicken (2014); Tay (2003); Jung *et al.* (2011); Beckert *et al.* (2012)

[9]Numbers as of March 2018.

[10]Pilny *et al.* (2017) provide a detailed overview about the German SHI and characteristics of its clients.

insurance nonworking spouses and dependent children under 25 years are covered free of charge. Further exemptions from insurance premiums apply also for students and unemployed. Specific groups of the population may opt out of SHI and buy substitute PHI or remain publicly insured as voluntary members (i.e., high-income earners), self-employed and civil servants (Bünnings *et al.*, 2017). Due to historical reasons, each SHI only offer one standardized health plan, which by law comprises full coverage of healthcare services and free choice of healthcare provider for all types and levels of care. By contrast, PHI providers are allowed to offer different health plans with varying components (e.g., cost sharing). In general, PHI health plans also offer full coverage and include free hospital of treatment choice. However, PHI do not have to contract with healthcare providers and do not negotiate about tariffs and prices. The maximum fee providers may charge for the treatment of PHI clients is regulated by the German Federal Ministry of Health (Wasem *et al.*, 2004).

A number of legislations have been introduced in order to improve and maintain high quality of care among healthcare providers. For example, all providers are obliged to establish a quality management system based on continuous medical education for all physicians as well as a health technology assessment for drugs and medical procedures. Moreover, requirements for a minimum volume of complex inpatient procedures enforce hospitals to adapt to the development of new technologies. The overall treatment process as well as the outcomes are regularly controlled through a mandatory quality reporting system (Busse, 2008; Busse and Blümel, 2014).

Large parts of German hospital policy are decentralized to the level of the 16 federal state governments (Länder). In particular, the state governments are responsible for hospital planning; i.e., they can decide on the extent, location and specialization of hospitals in their respective region. To this end, each state assembles a hospital plan and schedules the allocation of hospital capacities, investment subsidies and, to some extent, quality requirements for particular departments (Karmann and Roesel, 2017; Pilny, 2017). Hospitals that are included in a state's hospital plan are, since 2006, by the German social law obligated to publish standardized quality report cards[11]. Individuals are free to choose healthcare provider for their next elective hospitalization among those hospitals included in a hospital plan, or those hospitals that contract with the SHI. The dissemination of hospital quality among the public is a key strategy used by policy makers in the competitive hospital market to stimulate choice among healthcare recipients.

The performance indicators in the standardized quality report cards are analyzed by independent and impartial institutes: the Institute for Quality and Patient Safety (BQS),

[11]Hospitals not included in a hospital plan can contract with the SHI. In this case they are also legally obligated to publish quality report cards. Together these hospitals comprise about 90 percent of all hospitals or 99 percent of all bed capacities in the market.

the Institute for Applied Quality Improvement and Research in Healthcare (AQUA), and state-level specialized groups, providing various services such as individual feedback for each hospital to assure the quality in the German healthcare market[12]. BQS was in charge for defining procedures or diseases to be used as quality measures and to sample the respective data (Busse *et al.*, 2009). However, the quality report cards contain various technical terms and operating numbers too complex to understand without medical knowledge. In order to give patients the opportunity to form an opinion about hospital quality in a more digestible format, several on-line hospital comparison portals were launched to provide a comprehensible hospital quality ranking for all prospective patients[13].

3 Data

3.1 Inpatient care data

Our empirical analysis uses patient-level data collected from hospital discharge records based on diagnosis-related group (DRG) reimbursement claims. The data covers a nationally representative sample of clients from a large German health insurance company, who were hospitalized between 2009 and 2012 and includes a wide range of patient characteristics and comprehensive information about medical symptoms and administered treatments during the hospital spell. Clinical procedures performed by hospital physicians are coded according to the German classification of medical operations and procedures *Operationen- und Prozedurenschlüssel (OPS-12)*. To identify deliveries in the hospital data we use the registered cause of each admission, classified according to the *World Health Organization's International Statistical Classification of Diseases and Related Health Problems (ICD-10)*[14].

Our population of interest is restricted to expectant mothers, aged between 18 to 51, who gave birth in a maternity clinic located in a German hospital. We exclude all deliveries that occurred in any hospital units other than the specialized departments such as a gynecology and delivery (in total 6,457 births or about 2% of the sample). By combining the OPS and ICD codes, we identify and extract patients in the data with a singleton hospital delivery, in total around 250,000 deliveries. The hospital discharge data

[12]BQS managed the development and implementation of the external quality assurance system in Germany from 2001 to 2009 after which AQUA took over responsibility of this task.

[13]One popular hospital search portal is Weisse Liste, which is administered and maintained by the independent Bertelsmann Foundation and can be reached at https://www.weisse-liste.de

[14]Specifically, to identify deliveries we rely on ICD-10 codes: O80 (spontaneous delivery), O81 (delivery by forceps and vacuum extractor) O82 (delivery by cesarean section). We do not include multiple births in our analysis as they are considered risky deliveries and subject to additional patient choice restrictions.

furthermore allow us to describe the medical condition of each patient. We account for patient case-mix in terms of baseline health status using the Elixhauser index (Elixhauser *et al.*, 1998), computed from secondary diagnoses provider in the hospital data[15].

3.2 Quality data

We merge the inpatient data described in the previous section to hospital-level information on both objective (OQ) and subjective (SQ) quality measures. These indicators are obtained from publicly available quality report cards, which all hospitals are by law required to provide, and a survey of patient satisfaction conducted by Techniker Krankenkasse, a large German statutory health insurance company, respectively. In order to as closely as possible match the quality information that prospective patients use, we adhere to the criteria that the largest provider search platform in Germany, *weisse-liste.de*, base its hospital ranking on[16].

One important feature of the quality data is that it is reported biannually while we base our analysis on annual information from the hospital discharge data. However, this is not a problem since it merely implies that the information prospective patients have access to is only updated every second year. Hence, for each year where quality was not updated, we simply impute the previous year's quality for each hospital.

Below we give a brief description of the different quality indicators we use in our analysis.

Quality report cards

The hospital quality reports include detailed information on numbers of cases and procedures performed for each department. Furthermore, they also provide an overview of available medical and nursing services, existence of special departments and equipment, and a set of quality indicators measuring the structure, process, and clinical outcomes in the hospital. We employ three OQ indicators that account for quality of mandatory services in the maternity clinic. For consistency and ease of interpretation, we redefine these quality indicators in our empirical analysis so that a more positive value of the indicator always corresponds to higher quality. In addition, we include a set of indica-

[15]The Elixhauser Comorbidity Index (ECI) distinguishes 31 different comorbidities and is often used as a risk-adjustment tool to predict hospital resource use and in-hospital mortality. For a list of comorbidities we include in our analysis, see Table A.1 in Appendix A.

[16]The quality data we use is also the basis for the information provided on *weisse-liste.de*. Pross *et al.* (2017) show that this online platform is frequently used for provider search in Germany. Although our main empirical specification does not fully correspond to the information on *weisse-liste.de*, we have performed sensitivity analyses where our quality indicators are defined exactly as in the provider search platform, yielding qualitatively similar results. See Table A.2 in Appendix A.

tors for available services that a given clinic offers in addition to mandatory maternal services. These are categorized into medical and nursing services and care specialties, respectively. Figure 1 presents the hospital distribution of the OQ indicators we include in our analysis. We explain and define the different quality indicators in turn below.

- *Decision-to-delivery interval (DDI):* In some cases an emergency cesarean section is necessary in order to avoid irreversible damages for the infant (e.g., due to a lack of oxygen). The time span between the decision made for such an emergency cesarean section and the delivery of the infant is termed decision-to-delivery interval (DDI). According to current recommendations by the German Association for Gynecology and Obstetrics, an emergency cesarean section must be performed within 20 minutes of the decision (German Association for Gynaecology and Obstretics, 1995). Hospitals may improve their process structure and organization through a reduction of DDI, for example, by providing stand-by facilities or staff for emergency duties. DDI is a process quality indicator calculated as

$$\text{DDI} = \frac{\text{All deliveries with DDI below 20 minutes}}{\text{All deliveries with emergency cesarean section}}. \tag{1}$$

  The higher this ratio is for a hospital, the better is the hospital's quality. The upper left panel of Figure 1 shows that almost all hospitals comply with DDI below 20 minutes, i.e., a DDI indicator near unity.

- *Availability of pediatrician:* This process indicator refers to deliveries of premature infants with a gestational age of less than 37 weeks. In such cases, a pediatrician should attend the delivery and, if needed, provide necessary medical treatment to the infant. This indicator is calculated as

$$\text{Pediatrician} = \frac{\text{Availability of pediatrician}}{\text{All live births with gestational age} < 37 \text{ weeks}}. \tag{2}$$

  The higher the ratio of pediatrician attendance of premature births, the better is the hospital's quality with respect to this indicator. The distribution of this indicator is depicted in the upper middle panel of Figure 1. The figure shows that, while most hospitals have a pediatrician attending the majority of premature births, a substantial proportion do not appear to have this option available at all.

- *Perineal tear trauma:* A perineal tear trauma is a type of obstetric trauma which can be either light and curative (degree 1-2), or heavy and potentially chronic (degree 3-4). The heavy perineal tear trauma is considered a preventable condition and, as such, a commonly used patient safety indicator for hospital quality. Since

assisted, surgical, and multiple births are generally more risky deliveries, this indicator is calculated as the ratio of the prevalence of heavy perineal tears among all spontaneous singleton births

$$\text{Perineal tear trauma} = \frac{\text{No heavy perineal tear trauma}}{\text{All spontaneous singleton deliveries}}. \tag{3}$$

The higher this ratio is, the better the hospital's quality. The upper right panel of Figure 1 indicates that this outcome indicator exercises some variation across hospitals, although hospital trauma shares are unlikely to be above 0.05.

- *Medical & Nursing services:* The medical and nursing services (M-N Services) comprises a maximum of five services a hospital may offer to pregnant women: puerperium exercises; prenatal classes; infant care classes; breastfeeding advice; and further special service offers by midwives (e.g., water births). Depending on the number of services offered by a hospital, this score ranges between zero to five. Figure 1 shows that there is considerable variation across the maternity clinics with respect to the availability of these services.

- *Care Specialties:* Care specialties and medical services offered by the maternity clinic comprise a maximum of six services a hospital may offer: prenatal diagnosis; surgery for easing the delivery; assistance for high-risk pregnancies; advice for high-risk pregnancies together with a gynecologist; examination of diseases during the pregnancy, while delivery, and while puerperium; (out-patient) delivery without a stay at the maternity clinic. This score ranges between zero to six. Also for this indicator, Figure 1 shows substantial heterogeneity across maternity clinics.

[Figure 1 about here]

Patient satisfaction

We also link our inpatient data to survey information on patient satisfaction with the hospital and treatment. Starting from 2006, a large public German health insurer, Techniker Krankenkasse (TK), have biannually surveyed their clients' experiences with the care they received during their last hospital visit (Techniker Krankenkasse, 2010)[17]. The questionnaires are sent to a random sample of clients, with exceptions for individuals older than 80 years or in need of long-term care[18]. The survey consists of 41 questions

[17] Techniker Krankenkasse, founded in 1884, is one of Germany's largest social health insurance funds with a market share of about 14%, or 10 million clients (as of 2018).

[18] For each hospital between 150 and 1,000 patients were asked to participate in the survey. The response rates were quite high. For example, in 2010 more than 61% of surveyed patients responded

partitioned into five categories where the participant is asked to rate the satisfaction with the hospital visit, the results of treatment, the medical and nursing care, the communication of the hospital staff, and the organization and accommodation during the stay. Each question was evaluated by assigning points ranged between 0 and 12 where more points indicated higher satisfaction. For each category the answers have been rescaled to lie within the unit interval. Figure 2 show the distributions for each satisfaction category, respectively.

[Figure 2 about here]

One potential issue with jointly including all the five questions of the TK survey in our econometric model is that they are likely to be highly internally correlated. For example, a patient who was unsatisfied with the treatment she received is also likely to respond more negatively with respect to overall satisfaction. A correlation matrix of the five SQ indicators is provided in the first panel of Table 1 and confirms our suspicion: all correlations across the different satisfaction categories are very strong. As a comparison, the middle panel of the table reports the correlation coefficients across the different OQ indicators, showing much weaker correlations. Finally, the bottom panel of Table 1 reports the correlations between OQ and SQ indicators. Interestingly, the correlations are typically negative, implying that hospitals with high reported OQ may perform worse in terms of SQ and vice versa.

[Table 1 about here]

Due to the high correlations across the SQ indicators, we apply a principal component analysis (PCA) to extract the information content of the five survey categories and summarize it into one single satisfaction index score[19]. Since results from estimation will be interpreted in units of standard deviations from standardized coefficients, the exact scaling of the variable is unimportant. Figure 3 illustrates the distribution of the composite subjective quality (CSQ) score.

[Figure 3 about here]

(Pilny and Mennicken, 2014). However, the results were only reported when at least 60 questionnaires were fully completed. In 2015, 1,138 hospitals were able to comply with the requirements. We account for missing quality information by including a dummy variable for each hospital where satisfaction data is unavailable.

[19]Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. In our case, the number of principal components turns out to equal exactly one.

3.3 Distance from hospital and choice sets

To measure the geographical distance for a patient to a hospital with maternal care capacity, we use the 5-digit postal code of patient's registered home and the postal address of each hospital, both of which are available in our data[20]. We estimate both the travel distance and the travel time for each patient-hospital combination using geocoding API software from Google® and Open Source Routing Machine (OSRM)[21].

The left panel of Figure 4 presents the distance distribution from each patient's home to the closest hospital in our sample. The resulting distribution is highly right-skewed with a range between 0 and 30 kilometers and a mean of 8.4 kilometers. In addition, the right panel of the figure shows the distribution of the *excess* distance patients travel between the closest and the chosen hospital. Although the mean of the excess distribution is only 3.9 kilometers, it has a substantial range. For example, more than ten percent of expectant mothers travel at least ten kilometers more than necessary to give birth. In other words, a substantial share of patients in our sample travel to a hospital located at more than twice the average distance to the closest hospital. This comparison suggests that patients value other factors than just geographical distance when choosing hospital.

[Figure 4 about here]

In order to estimate our choice model described in the next section, we define a choice set (i.e., a local hospital market) for each patient as the ten closest located hospitals based on the individual's place of residence[22]. Figure 5 shows a histogram of the share of patients in our sample who gave birth in their closest, second closest, etc., up to the tenth closest hospital, respectively. In addition, the bar farthest to the right in the figure displays the residual share of patients who chose a hospital located outside the choice set. Around 44% of patients chose to give birth in their closest hospital after which a gradually declining share chose to give birth in more distant hospitals. Approximately 9% of patients chose a hospital outside of the choice set[23].

[Figure 5 about here]

[20] This approach follows, e.g., Hentschker and Mennicken (2015, 2017); Mennicken *et al.* (2014) and implicitly assumes that patients and travels from the geographic centroid of each 5-digit postal code area corresponding to its geographic center. Since there are about 8,200 postal codes in Germany (implying that each postal code comprises a very small geographical area), we consider this assumption innocuous.

[21] For a documentation of the latter resource, see http://project-osrm.org/ and Huber and Rust (2016). We exclude a few cases where measuring the distance to a hospital was not possible, such as patients living on an island without a road connection to a hospital.

[22] Since the level of detail of our gecoding data is based on postal codes, individuals living in the same postal code area will be given the same choice sets.

[23] We have evaluated the robustness of our results to the definition of choice sets by estimating separate models also for five and fifteen choices, yielding similar results. Figure A.1 in Appendix A shows the respective choice distributions for the different choice set definitions.

Figure 6 shows two maps of Germany describing the distance to (left panel) and the density of hospitals with maternal care facilities (right panel) on the postal code area level, respectively. The left panel reveals that residents in most parts of the country have less than 20 kilometers to the nearest maternity clinic. The right panel shows a heat map of the number of hospitals with a maternity clinic within a 50 kilometers radius, where darker areas corresponds to more choices. As expected, the metropolitan areas of North Rhine-Westphalia, Hamburg, Berlin, Frankfurt, Stuttgart and Munich typically all have more than 50 choices while the sparsely populated areas in particularly Eastern Germany often have less than five. This highlights the need to control for choice set characteristics, such as average hospital distance and population density in our empirical analysis.

[Figure 6 about here]

3.4 Sample summary statistics

Table 2 reports summary statistics of the variables in our sample for different levels of data aggregation. From upper-left to lower-right, the columns refer to information on the patient, choice-set, hospital and closest hospital levels of aggregation, respectively. Around one-third of the roughly 250,000 individuals in our sample were admitted to the hospital for an emergency delivery. For emergencies it is likely that patients do not have full discretion in choosing hospital, for example if a hospital with emergency room capacity is deemed necessary by paramedics. To account for this, we retain emergency cases in our sample but include an indicator variable for whether the hospital admission was coded as an emergency in our regression models. We also adjust for other factors that may have affected the individual's choice of maternity clinic, such as whether the admission occurred on the weekend, during rush hour (i.e., between 6 am and 10 am), whether the patient lived in a rural or an urban area, case-mix controls for the number of Elixhauser co-morbidity indicators, and whether the birth was considered risky. Summary statistics for these variables are reported in the two upper panels of Table 2, corresponding to the level of the patient (left) and the choice set (right)[24].

Table 2 also provides some statistics on the aforementioned distance variables. Specifically, although the average patient in our sample had approximately eight kilometers (12 minutes) from her home to the closest hospital, she chose a hospital at around 12 kilometer (16 minutes) from her home. Around half of the expectant mothers did not choose their closest hospital, but resorted instead to a hospital which was located at an additional three kilometers distance, on average. The corresponding figures for the choice

[24]The number of choice sets are greater than the number of postal codes because the number of hospitals changes over time due to openings, closures and mergers. The implication is that choice sets, in contrast to postal codes, are also time-varying.

sets closely resembles the individual level counterparts, except for a larger share of rural choice sets and increased distances and travel times to the closest and chosen hospitals, respectively. These differences make intuitive sense, since the number of patients should be proportional to the population density within the different choice sets. We account for such heterogeneity by including these variables as additional regressors in our empirical analysis.

The two lower panels of Table 2 present hospital-level summary statistics of the quality indicators we include in our analysis. The left panel refers to the individual hospitals while the right panel refers to the closest hospital in each choice set (where the same hospital can be included several times). Around 22% of the maternity clinics lacked information about SQ (see footnote 18). To handle the missing data while simultaneously keeping the choice sets intact, we impute a zero value for each observation for which quality information is not available and add a dummy variable in our econometric model to distinguish these missing values from "true" zeros. In other words, the impact of missing hospital information will be captured by these additional quality indicator specific intercepts.

Finally, we also adjust for a set of other hospital-specific factors related to the performance of a hospital, such as ownership type, number of beds, whether the hospital is a teaching or a university hospital, and a set of capacity-related variables such as the number of midwives and share of specialized physicians. The main reason for why we make these covariate adjustments is to account for the possibility that prospective patients make their choices of hospital based on other criteria than our quality indicators.

[Table 2 about here]

4 Econometric framework

To empirically study the relationship between expectant mother's choice of maternity clinic and reported quality, we consider two econometric models estimated from our sample as described in the previous section. We initially estimate a simple linear probability model (LPM) for choosing the closest provider in each patient's choice set as a function of the hospital's reported quality. This model allows us to obtain an easily interpreted reduced form estimate of the impact of quality on the choice of hospital[25].

Formally, our data set is a repeated cross-section consisting of $i = 1, ..., N$ patients, $t = 1, ..., T$ years, and $k_j = 1, ..., K_j$ hospitals for each of the $j = 1, ..., J$ choice sets[26].

[25] We model a LPM in this analysis because we are primarily interested in the signs of the estimated coefficients, which are the same whether we use a LPM or a non-linear model, such as logit, to estimate equation (1).

[26] Each choice set includes an equal number of hospitals, but hospitals may be part of several choice

Our LPM is thus defined by

$$Closest_{ijt} = \alpha_0 + f(d^c_{jt}; \alpha_d) + q^{c\prime}_{jt}\beta_q + X'_{ijt}\Theta_X + Z^{c\prime}_{jt}\Theta_{Z^c} + \bar{Z}'_{jt}\Theta_{\bar{Z}} + \epsilon_{ijt}, \tag{1}$$

where $Closest_{ijt}$ is a binary indicator for whether a patient chose the closest hospital in her choice set[27]. Similarly, d^c_{jt} and q^c_{jt} indicate the distance (scalar) and quality (vector) of the closest hospital in the individual's choice set, where $f(\cdot)$ is a cubic polynomial function of d^c_{jt} with corresponding parameter vector α_d. Furthermore, X_{ijt}, Z^c_{jt}, and $\bar{Z}_{jt} = N^{-1}\sum_k z_{jkt}$ are vectors of patient, closest hospital, and average choice set specific variables (as reported in Table 2), respectively. Finally, ϵ_{ijt} is an assumed random regression error term. Since the quality indicators, our main regressors of interest, only vary on the choice set level, we cluster the standard errors on this level to account for any residual correlation across individuals within the same choice set. We are primarily interested in the signs of the $\hat{\beta}_q$ vector, which will inform us about whether an improvement in a specific quality indicator of the closest hospital increases the likelihood of choosing it relative to the other hospitals in the same choice set. Since we have redefined all quality indicators in a way that higher values are synonymous to better quality, we expect all coefficients to be positive[28].

Inference from the LPM in equation (1) is generally uninformative about the trade-off between distance and quality. Therefore, we also consider a structural econometric framework for hospital choice based on a random utility model, which we estimate by means of a multinomial logit model[29]. The advantage of this approach is that it allows us to derive and compute an economically relevant parameter: the additional distance a patient is willing to travel in exchange for an increase in reported quality of a hospital located further away.

The random utility model specifies

$$U_{ikt} = V_{ikt} + \xi_{kt} + \mu_{ikt} \quad \text{for } (i,k) \in j, \tag{2}$$

where the utility, $U(\cdot)$, for individual i of choosing hospital k in year t is a linear function of observable hospital characteristics V_{ikt}, unobservable hospital characteristics ξ_{kt} and

sets. Therefore the number of hospitals is strictly lower than $K \times J$. Choice sets may change over time if existing hospitals are shut down or new hospitals enter the market (hence the t subscript in equation (1)). However, there are few changes in the existing structure over the studied time period.

[27] That is, $Closest_{ijt}$ evaluates to one if the chosen hospital k_j satisfies $k_j : d_{jkt} = \min(d_{jt})\ \forall\ k_{jt} \in (j,t)$.

[28] We have also estimated models where we, instead of including the absolute quality of the closest hospital, use the relative quality compared to the average quality in the choice set. This modification does not change our results to any important extent.

[29] Specifically, we have estimated models for both alternative-varying and alternative-fixed regressors, but focus on the former (conditional) logit model when reporting our results. The estimated parameters do not differ to any important extent with respect to model choice.

unobserved individual heterogeneity, μ_{ikt}. Assuming that μ_{ikt} is i.i.d. and type I extreme value distributed, the probability that patient i chooses hospital k can be written on the logistic form as (see, e.g., Cameron and Trivedi, 2005)

$$p_{ikt} = \Pr[y_{it} = k] = \exp\left(V_{ikt} + \xi_{kt}\right) \left[\sum_{k' \in j} \exp\left(V_{ik't} + \xi_{k't}\right)\right]^{-1}, \quad k = 1, ..., K_j, \tag{3}$$

where the dependent variable y_{ikt} is defined as

$$y_{ikt} = \begin{cases} 1 & \text{if } y_{it} = k \\ 0 & \text{if } y_{it} \neq k. \end{cases} \tag{4}$$

Individual utility is assumed to be represented by

$$\begin{aligned} U_{ikt} = \sum_{p}^{P} \gamma_{pt}^{q} q_{kpt} + \sum_{s}^{S} \gamma_{st}^{d} d_{ikt}^{s} + \sum_{p}^{P} \sum_{m}^{M} \gamma_{pmt}^{qx} q_{kpt} \tilde{x}_{imt} \\ + \sum_{s}^{S} \sum_{m}^{M} \gamma_{mst}^{dx} d_{ikt}^{s} \tilde{x}_{imt} + \sum_{l}^{L} \gamma_{lt}^{z} z_{klt} + \nu_{ikt}, \end{aligned} \tag{5}$$

where q_{kpt} refers to the pth quality indicator and d^s to the sth polynomial order for the (cubic) distance relation. Furthermore, $\tilde{x}_{imt} = x_{imt} - \bar{x}_m$ is the mean-centered value of the mth individual characteristic with $\bar{x}_m = N^{-1} \sum_t \sum_i x_{imt}$ and z_{klt} is the lth hospital specific variable reported in Table 2. The vector $\gamma = (\gamma^q, \gamma^d, \gamma^{qx}, \gamma^{dx}, \gamma^z)$ comprises the set of coefficients to be estimated[30]. Finally, the joint error term $\nu_{ikt} = \xi_{kt} + \epsilon_{ikt}$ is assumed to be i.i.d. conditional on the included individual- and hospital-level covariates[31].

Mean-centering the individual patient characteristics allows us to both control for potential confounding factors and interpret the estimated γ_{pt}^{q} and γ_{st}^{d} as marginal utilities with respect to quality and distance for a patient with average characteristics in a given year. From the model, described by equations (2)-(5), we can produce an estimate of the willingness to travel (WTT) for a representative patient to a hospital with a one standard

[30] We do not allow for choice set-specific variables in this model but instead assess heterogeneity by estimating models conditional on average quality and distance.

[31] Endogeneity concerns could arise if, e.g., private or teaching hospitals are perceived by individuals as being of different quality than public or non-teaching hospitals or if lower quality hospitals are leaving the market due to fierce competition. We assume that our included hospital specific variables accounts for the former concern, and that the observation that few hospitals leave the market suggests that the latter is unlikely to be a serious problem in the present context.

deviation increase in the pth reported quality measure as (see, e.g., Moscelli *et al.*, 2016)

$$\begin{aligned} WTT_{pt} &= \sigma_p \frac{\partial d_{ikt}}{\partial q_{kpt}} = \sigma_p \left(-\frac{\partial U_{ikt}/\partial q_{kpt}}{\partial U_{ikt}/\partial d_{ikt}} \right) \\ &= \sigma_p \frac{-\gamma^q_{pt}}{\gamma^d_{1t} + 2\gamma^d_{2t}\zeta_d + 3\gamma^d_{3t}\zeta_d^2}, \end{aligned} \tag{6}$$

where the second equality is the negative of the marginal rate of substitution and the third equality is obtained from differentiation of equation (5) with a cubic distance representation. σ_p is the standard deviation of the pth quality measure and ζ_d is the average distance to the chosen provider for all patients over all years. To obtain standard errors for the WTT, we apply the delta method (see, e.g., Cameron and Trivedi, 2005).

5 Results

We first present descriptive results on the relationship between quality and choice in our data. Figure 7 presents the distribution of patients according to the chosen hospital for each quality indicator from the best (1) to the worst (10) hospital in their choice set. With respect to pediatrician availability, medical and nursing services, and care specialties there is a clear visible positive association between quality and popularity of a hospital within choice sets. For the remaining quality indicators the patterns are less clear, although lower quality ranked hospitals are in general less popular.

[Figure 7 about here]

5.1 Linear probability model

Table 3 reports the results from the linear probability model for choosing the closest provider in the choice set as specified in equation (1). In column (1) all OQ indicators are included together with the cubic distance polynomial to the closest hospital, while SQ is included through each of the five satisfaction sub scores in the TK survey. In column (2), SQ is instead included using the constructed composite SQ score from the PCA. Finally, column (3) additionally includes the full set of patient, hospital and choice set control variables listed in Table 2.

As expected, choosing the closest provider is negatively associated with distance (disregarding from the negligible second and third order terms) and positively associated with the OQ indicators. Regarding the latter, all coefficients are highly statistically significant except for perineal tear trauma (all columns) and D-D-I (last column). The estimated coefficients of the satisfaction sub scores in column (1) are not not distinguishable from

zero for general satisfaction, satisfaction with treatment and satisfaction with information, but highly significant for satisfaction with accommodation and with care. However, the latter coefficient has a negative sign, highlighting the issue of multicollinearity across the satisfaction sub scores. When we instead include the composite SQ score in column (2) and (3) we obtain a positive and, in the latter case, also statistically significant point estimate of the SQ indicator. Hence, it appears that higher reported quality is associated with an increased probability of choosing the closest hospital in the choice set.

[Table 3 about here]

5.2 Conditional logit model

Table 4 reports the estimated coefficients from the conditional logit model, defined by equations (2)-(5), including the full set of controls. As in Table 3, SQ is included either through the satisfaction sub scores (column 1) or through the composite score (column 2)[32].

Again, choice of hospital is negatively correlated with distance and the higher order terms suggest a diminishing association as distance increases. Furthermore, all OQ indicators are positively correlated with choice of hospital and significant at the one percent level. Regarding the SQ indicators, the multicollinearity issue is again prevalent from observing the varying signs of the satisfaction sub scores in column (1), but once we include our composite SQ score the coefficient is positive and highly statistically significant.

[Table 4 about here]

The estimated coefficients from the conditional logit model are not directly conducive of a quantification of the effect of quality on choice. As such, we rely on equation (6) to estimate the average willingness to travel (WTT) of expectant mothers for an one standard deviation increase in each quality indicator. The results are presented graphically in Figure 8, in which the left panel refers to the point estimates from the conditional logit model (for comparison) and the right panel refers to the WTT estimates. A one standard deviation increase in reported quality for the three process quality indicators (D-D-I, perineal tear trauma and pediatrician availability) are associated with increases in the WTT of between 0.7 to 1.6 kilometers, while an equivalent increase in reported quality for the service categories increases WTT by 0.7 (care specialties) and a substantial 4.2 (medical and nursing services) kilometers. With respect to the composite SQ score, the figure is 0.7 kilometers and hence closer to the lower bound of the estimates from the OQ indicators. Hence, the range of WTT is substantial and highly dependent on

[32]Results for choice set sizes 5/10/15 are provided in Table A.3.

the specific quality indicator[33]. As a relevant comparison, the average patient is willing to travel between one-tenth to one-third of the distance to the closest hospital to reach a hospital of higher quality. Given that the mean difference between the closest and the chosen hospital is about 3.9 kilometers (see Table 2), this does not appear to be an unreasonable quantification of the WTT.

[Figure 8 about here]

An interesting finding from our analysis is that prospective patients react to SQ information also independently of the set of included OQ indicators. The results from the correlation analysis between the objective and subjective quality indicators, reported in Table 1, also suggested an negative correlation between the two dimensions of quality within hospitals. Hence, in addition to the substantial range in the magnitude of the response of expectant mothers across quality indicators presented in Figure 8, there also seem to exist a trade-off between increasing certain dimensions of quality which comes at the cost of other dimensions. For example, hospitals with high clinical excellence in elective treatments, such as low risks of mortality or complications, perform worse with respect to "softer" dimensions of quality, such as personal comfort, staff friendliness, etc., that might affect patient experiences and contribute to post-treatment recovery in ways that are not captured by physical health events.

6 Conclusion

In this paper we study patient choice of hospital with respect to both objective and subjective information about provider quality in the context of maternal care in Germany. Objective quality indicators are obtained from mandatory hospital quality report cards and subjective indicators are based on patient satisfaction scores from a large, nationwide hospital survey. The quality information is linked to hospital discharge records including information on the place of residence of both patients and hospitals. We use the data to estimate econometric choice models to quantify the additional distance expectant mothers are willing to travel to give birth in a hospital of higher reported quality. Our results indicate that individuals are on average willing to travel between 0.7 and 4.2 additional kilometers, depending on quality indicator, to obtain a one standard deviation increase in reported quality. Both objective and subjective indicators are independently associated with increases in the probability of choosing hospitals with higher reported quality.

[33]We have also performed the same analysis using travel time as distance metric, yielding a corresponding WTT interval of 0.5–5.5 minutes.

Our findings contribute to the existing literature on the determinants of consumer choice of healthcare provider. In line with previous findings, we obtain empirical evidence that prospective patients are responsive to quality; other papers have estimated a willingness to travel (WTT) of at most 0.9 kilometers (Gutacker *et al.*, 2016) or 0.7 kilometers (Moscelli *et al.*, 2016) for a one standard deviation increase in objective quality measures related to elective hip replacement surgery. While we find similar WTT estimates for the majority of the quality indicators we analyze, we also report an average WTT as large as 4.2 kilometers for a standardized increase in the number of medical and nursing services in a hospital. One reason for this strong patient response could be the importance that medical and nursing services can have for both the mother's and the child's health and wellbeing both pre, during, and post delivery[34].

Interestingly, we also find that patients value not only objective but also subjective quality information. This is an important finding since it highlights that there are dimensions of quality of care that are not subsumed within standard objective quality metrics despite their richness and variety. Furthermore, subjective quality is in general negatively correlated with the objective quality indicators within a hospital, suggesting that hospitals with high clinical excellence, such as low risks of mortality or complications, perform relatively worse with respect to "softer" dimensions of quality, such as personal comfort, staff friendliness, etc., that might contribute to patient well-being in ways that are not captured by physical health events. Thus, our results indicate that different quality measures may not necessarily be substitutes and could even involve conflicting information.

Why do patients also value subjective information about quality in addition to more conventional and validated clinical measures of hospital performance? One potential explanation involves viewing quality as a multidimensional construct. Patient satisfaction scores may be regarded as measures of the overall quality of a provider with respect to a broad range of services, ranging from quality of technical equipment to the social treatment by physicians and nurses during the inpatient stay. In contrast, objective measures mainly provide information about one particular dimension of quality[35]. As a result, different quality measures may adhere to different aspects of quality. Both healthcare providers and social planners should hence consider complementing objective indicators with more subjective assessments in their quality reporting to capture a broader range of consumer preferences and thereby improve patient well-being.

[34] In Germany women tend to keep loyalty to the hospital where they gave birth. Anecdotal evidence is provided in e.g. Süddeutsche Zeitung (2017). Availability of such services may thus be important when making a long-term commitment to a hospital.

[35] An analogue can be found in the literature on the use of objective versus subjective health measures to assess overall individual health, where self-assessed health is often found to predict mortality independently of conventional objective health indicators (see, e.g., Idler and Benyamini, 1997).

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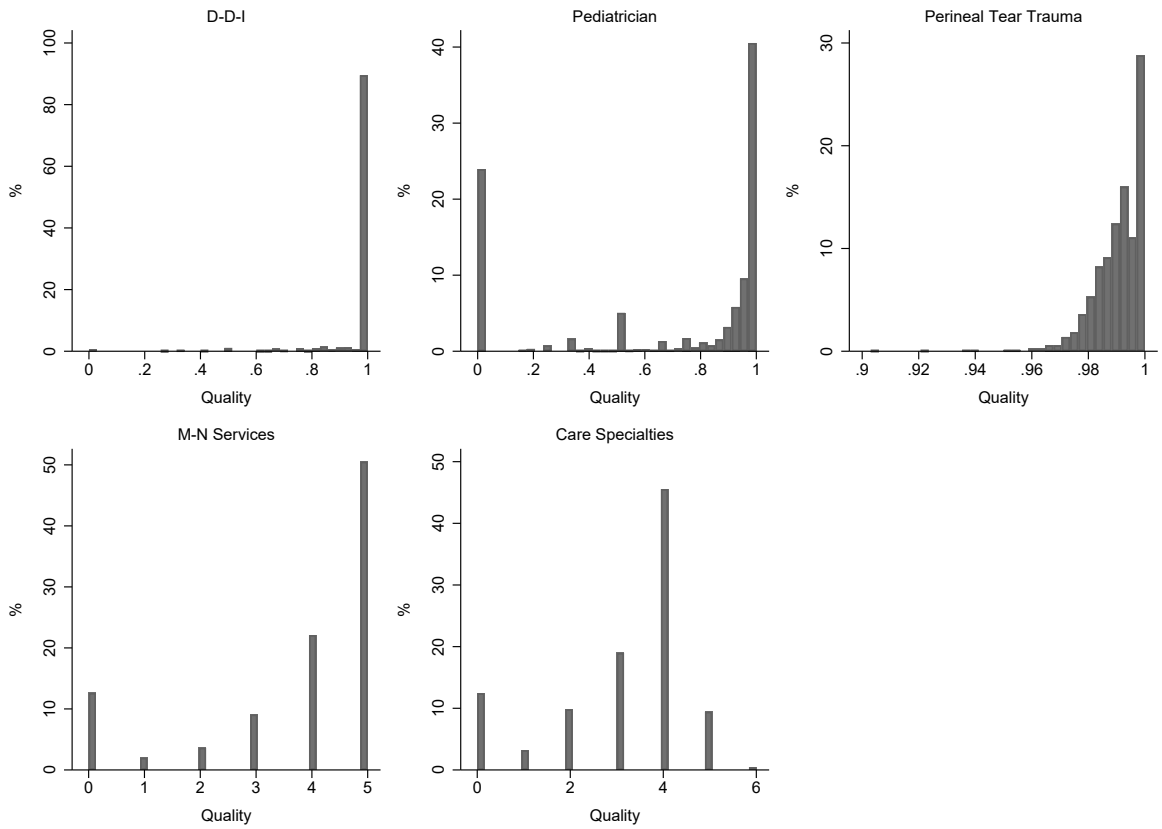
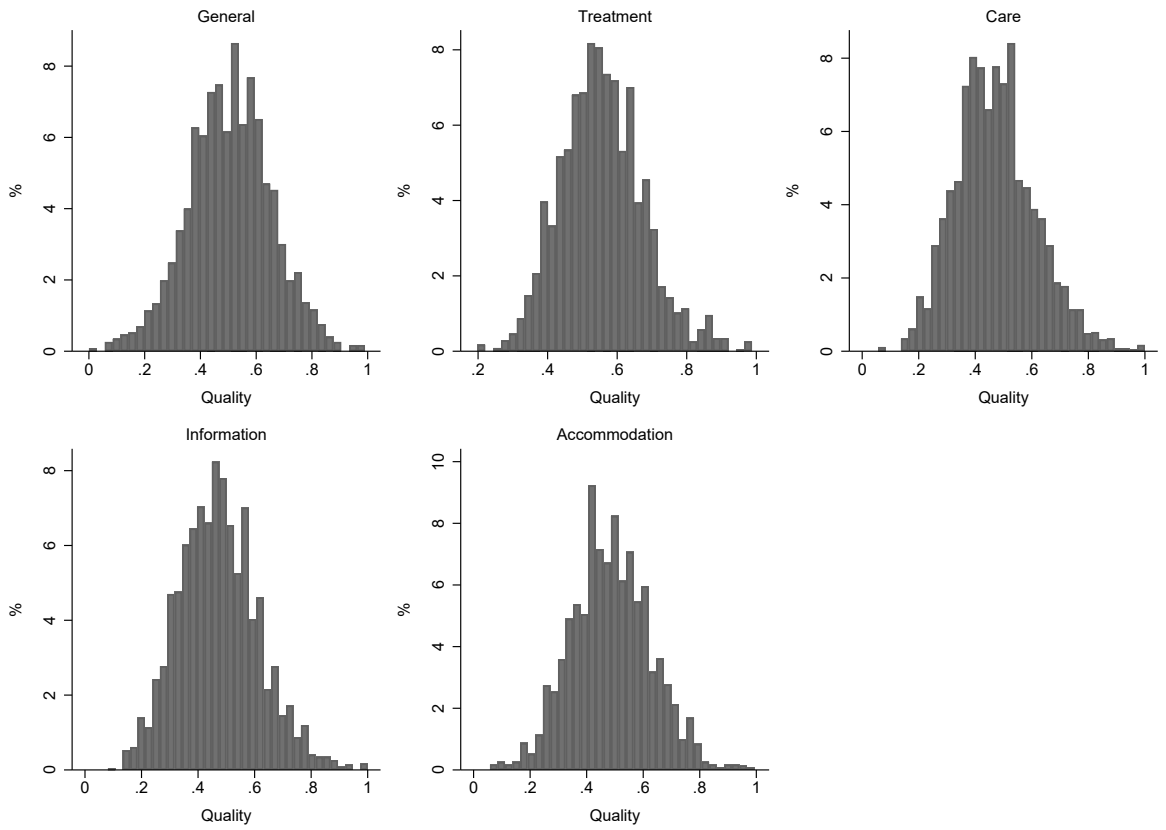
Tables and Figures

FIGURE 1.
Distribution of OQ indicators



NOTE.— The graph presents the distributions of the objective quality (OQ) indicators analyzed in the paper.

Figure 2.
Distributions of SQ indicators



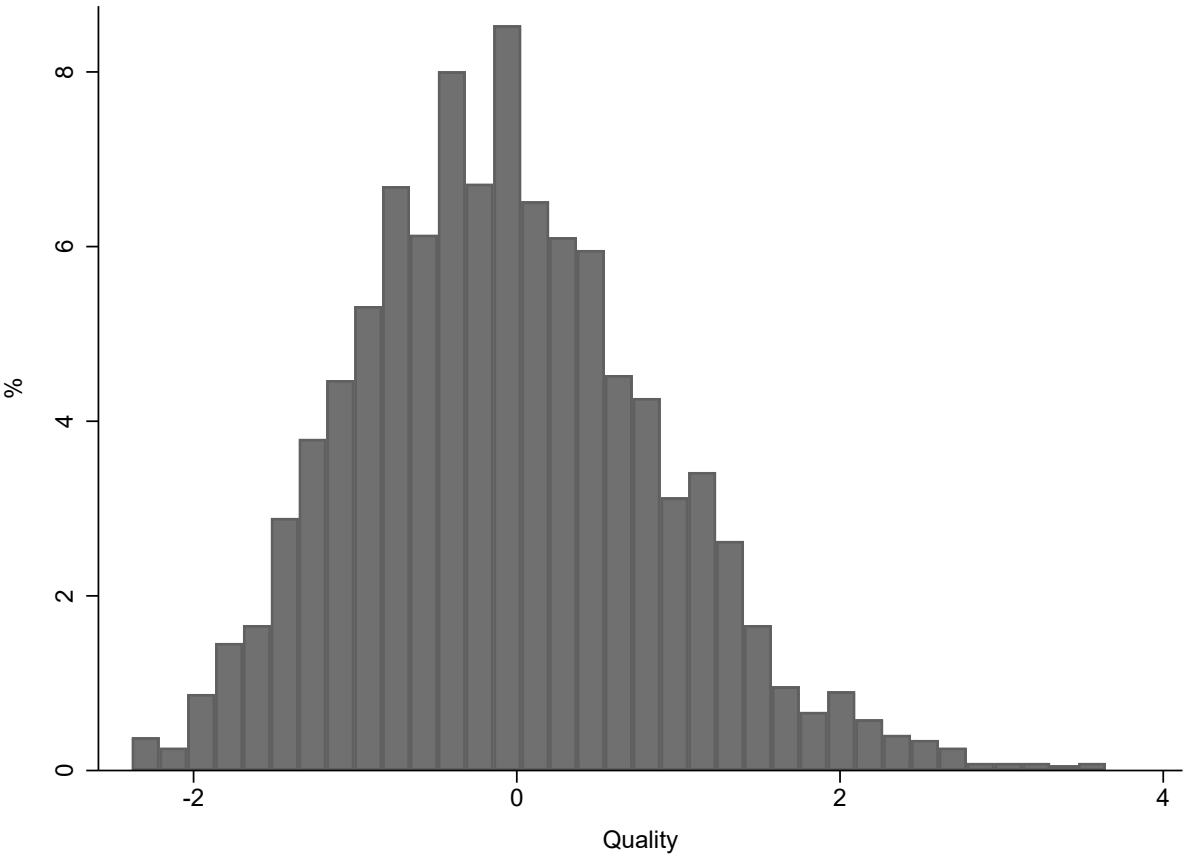
Note.— The graph presents the distributions of the subjective quality (SQ) indicators from the five categories of the TK patient satisfaction survey.

Table 1.
Correlation coefficients across quality indicators

I. Subjective quality (SQ)	General	Treatment	Care	Information	Accommodation
General	—				
Treatment	0.727***	—			
Care	0.872***	0.772***	—		
Information	0.860***	0.786***	0.937***	—	
Accommodation	0.823***	0.660***	0.822***	0.786***	—
CSQ score	0.894***	0.868***	0.963***	0.957***	0.889***
II. Objective quality (OQ)	**D-D-I**	**Pediatrician**	**Trauma**	**M-N Services**	**Care Specialties**
D-D-I	—				
Pediatrician	0.055***	—			
Perineal Tear Trauma	0.021	0.192***	—		
M-N Services	0.054***	0.220***	0.100***	—	
Care Specialties	0.013	0.285***	0.143***	0.521***	—
III. OQ/SQ	**D-D-I**	**Pediatrician**	**Trauma**	**M-N Services**	**Care Specialties**
General	-0.004	-0.152***	-0.046	0.044	-0.061*
Treatment	-0.064*	-0.275***	-0.099***	0.030	-0.117***
Care	-0.065**	-0.277***	-0.097***	0.034	-0.169***
Information	-0.050*	-0.253***	-0.098***	0.046	-0.134***
Accommodation	-0.044	-0.226***	0.005	0.006	-0.071**
CSQ score	-0.060*	-0.279***	-0.079**	0.032	-0.134***

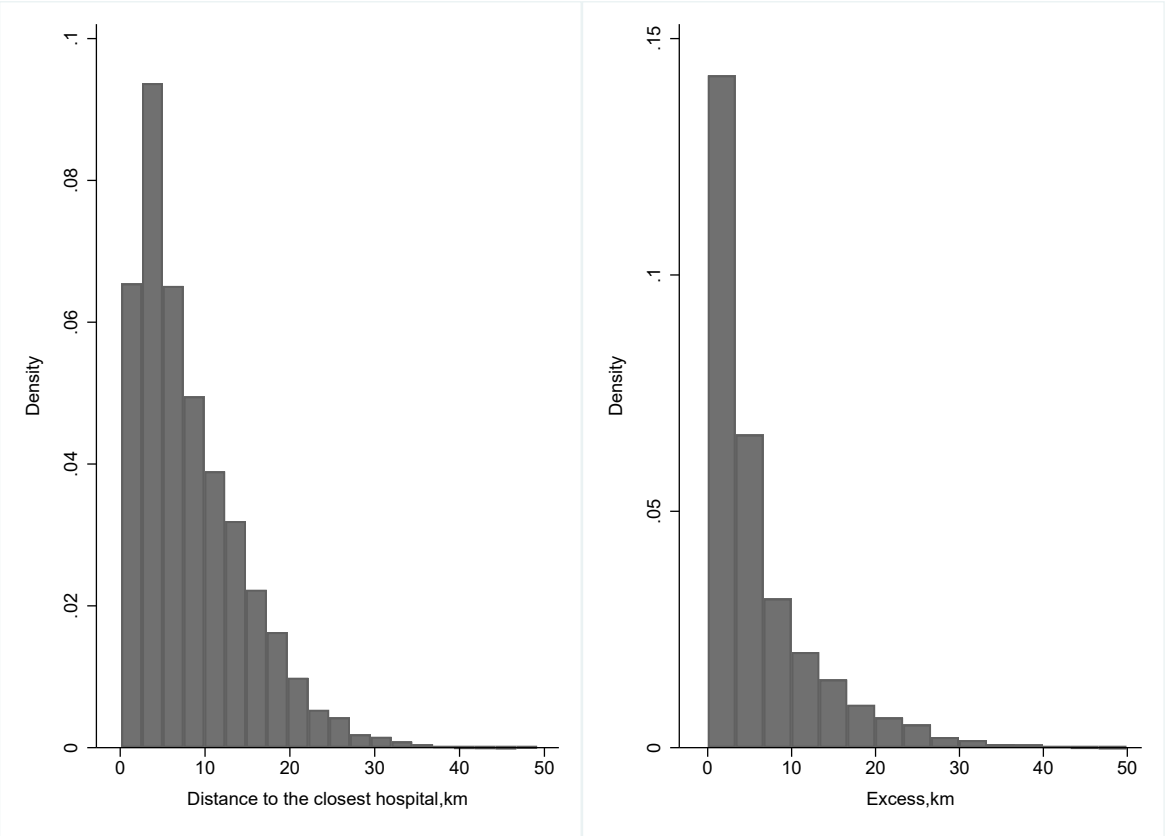
Note.— Table presents correlation coefficients of the included quality indicators. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 3.
Distribution of CSQ score



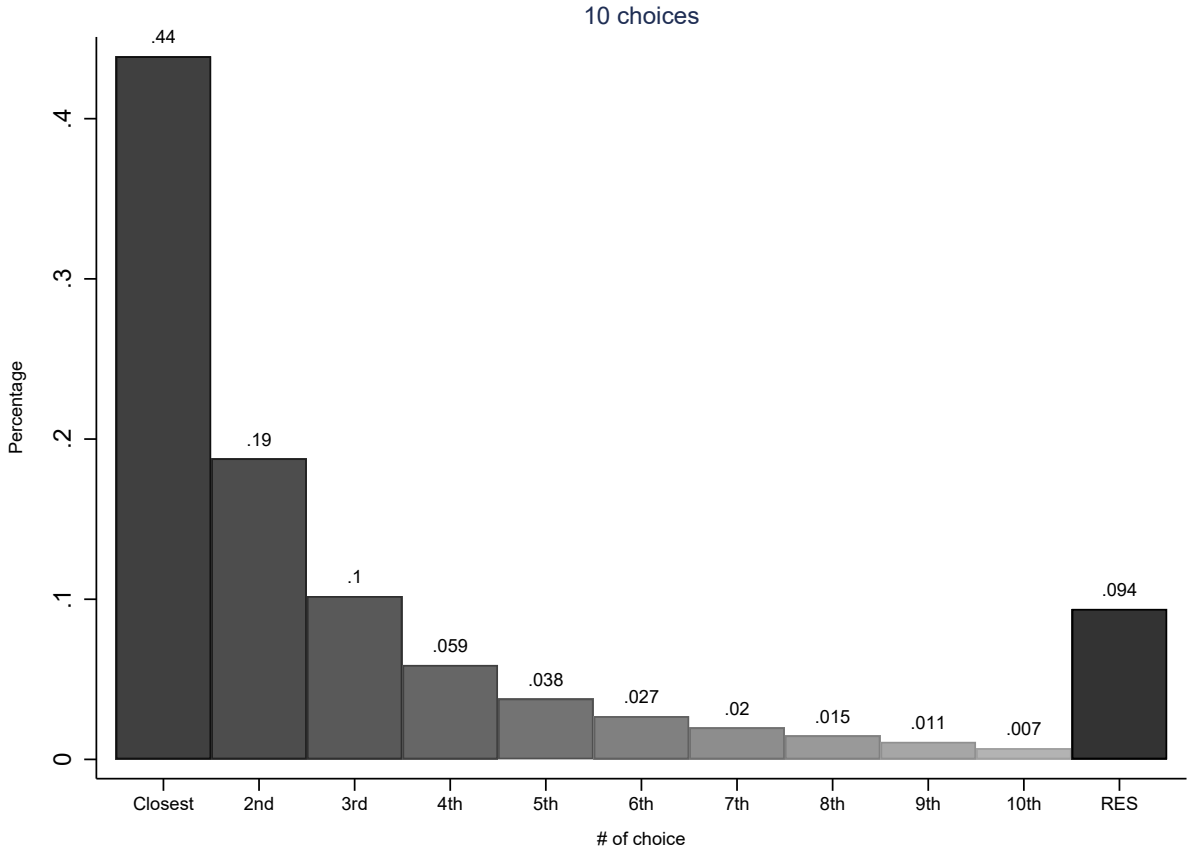
Note.— The graph presents the composite subjective quality (CSQ) score after application of principal component analysis (PCA) on the five subscores of the TK patient satisfaction survey, reported in Figure 2.

Figure 4.
Distributions of the distance to the closest hospital and excess distance to the chosen hospital



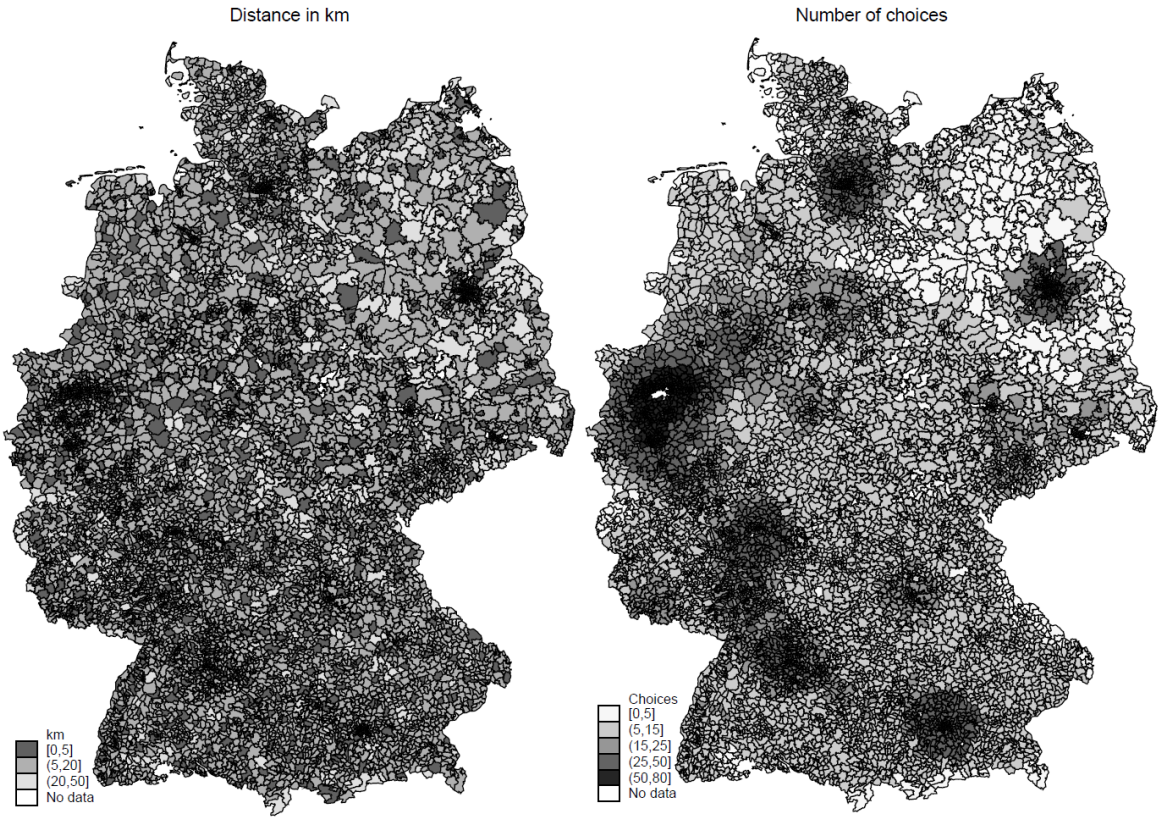
Note.— Excess distance is defined as the additional distance between the closest and the chosen hospital traveled by a patient.

Figure 5.
Distribution of choices ranked by hospital distance from patient home



Note.—The first choice in the choice set is the closest to the residence maternity clinic. The numbers on top of the bars indicate the percentage of individuals who made the respective choice.

Figure 6.
Distance to and density of hospital maternal care facilities in Germany



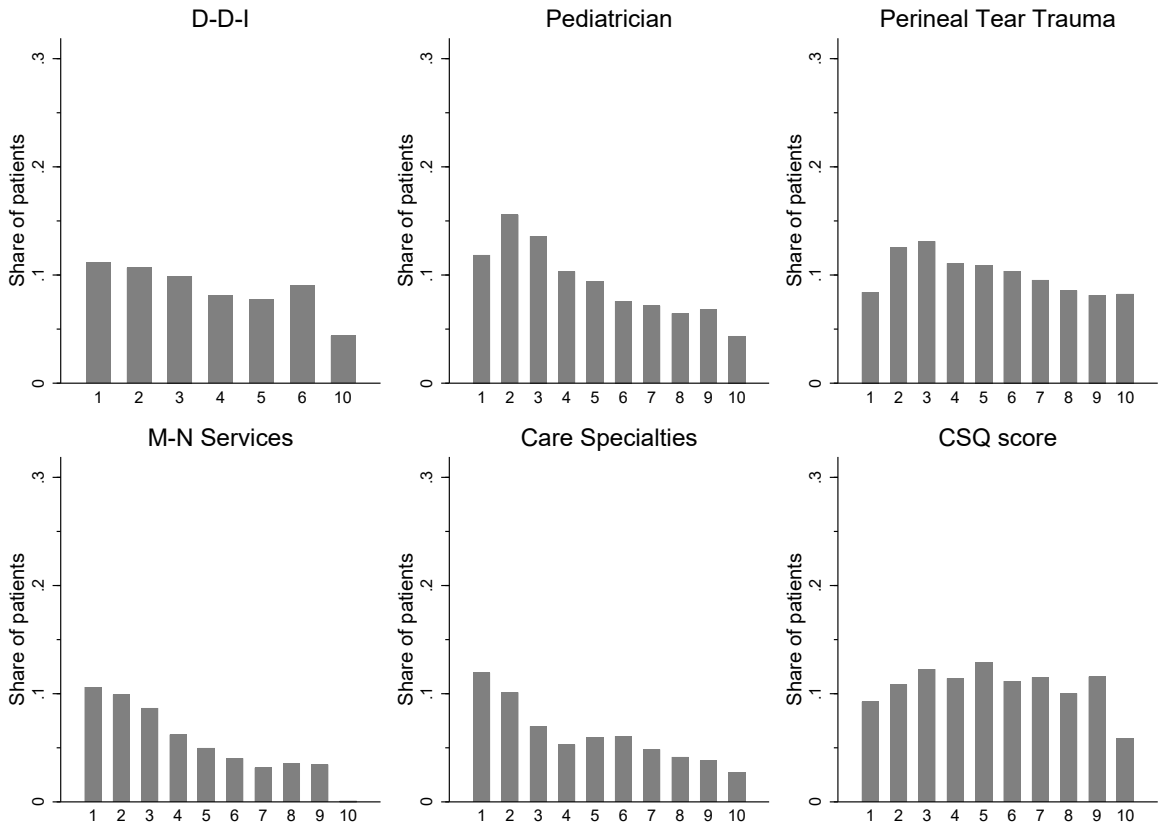
Note.—The map is divided by zip code areas. The left panel presents the distance in km to the closest maternity clinic. The right panel shows the number of choices within a 50 kilometers radius form the midpoint of the postal code area.

Table 2.
Descriptive sample statistics

	Patient		*Choice-set*	
	Mean	SD	Mean	SD
Patient characteristics				
Age in years	31.14	[5.05]	31.16	[2.42]
# Elixhauser conditions	0.17	[0.41]	0.15	[0.19]
If emergency	0.30	[0.46]	0.27	[0.30]
If weekend	0.23	[0.42]	0.23	[0.19]
If rush hour	0.37	[0.48]	0.37	[0.22]
If risky	0.04	[0.20]	0.04	[0.09]
Choice-set characteristics				
If rural postal code	0.27	[0.44]	0.42	[0.49]
If closest hospital chosen	0.48	[0.50]	0.48	[0.36]
Excess distance	3.93	[7.04]	4.92	[5.89]
Distance closest hospital (km)	8.40	[6.39]	11.69	[7.34]
Travel time closest hospital (min)	12.18	[7.85]	15.26	[8.80]
Distance chosen hospital (km)	12.34	[9.85]	16.61	[9.59]
Travel time chosen hospital (min)	15.69	[10.00]	19.46	[10.11]
Observations	248,063		13,256	
	Hospital		*Closest hospital*	
	Mean	SD	Mean	SD
Objective quality indicators (OQ)				
D-D-I	0.99	[0.08]	0.98	[0.09]
Pediatrician	0.32	[0.44]	0.48	[0.45]
Perineal Tear Trauma	0.99	[0.01]	0.96	[0.07]
M-N Services	3.78	[1.70]	3.89	[1.58]
Care Specialties	3.04	[1.46]	3.21	[1.40]
Subjective quality indicators (SQ)				
General	0.26	[0.27]	0.49	[0.37]
Treatment	0.29	[0.29]	0.48	[0.37]
Care	0.25	[0.26]	0.47	[0.36]
Information	0.25	[0.26]	0.48	[0.37]
Accommodation	0.25	[0.26]	0.45	[0.35]
Composite SQ Score	-0.03	[0.68]	-0.05	[0.69]
Hospital characteristics				
If public	0.42	[0.49]	0.33	[0.47]
If private	0.17	[0.37]	0.50	[0.50]
If university	0.03	[0.17]	0.02	[0.14]
If teaching	0.40	[0.49]	0.51	[0.50]
Birth-staff ratio	176.72	[136.88]	252.10	[92.34]
Share specialized physicians	0.56	[0.16]	0.41	[0.27]
# hospital beds	389.95	[345.94]	394.02	[353.90]
# hospital midwives	8.03	[7.82]	8.42	[8.04]
# hospital nurses	3.34	[5.84]	3.80	[5.08]
Observations	6,545		13,256	

Note.— Table presents descriptive statistics on different levels of data aggregation.

Figure 7.
Patient choice by hospital rank for different quality indicators



Note.— Graphs present the shares of patients who chose the best (1) to the worst (10) hospital (measured by the respective quality indicator) in their choice set, by quality indicator.

Table 3.
Linear probability model estimates for choosing the closest hospital

	(1)	(2)	(3)
Distance	-0.018***	-0.013***	-0.018***
	(-6.84)	(-4.89)	(-6.72)
Distance^2	0.000*	0.000	0.001**
	(2.22)	(1.63)	(2.93)
Distance^3	-0.000	-0.000	-0.000
	(-0.58)	(-0.18)	(-1.37)
D-D-I	0.083**	0.088**	0.054
	(2.70)	(2.67)	(1.72)
Pediatrician	0.110***	0.142***	0.113***
	(11.88)	(14.76)	(11.91)
Perineal Tear Trauma	0.001	0.094	0.091
	(0.01)	(1.65)	(1.68)
M-N Services	0.032***	0.027***	0.025***
	(11.92)	(9.76)	(9.24)
Care Specialties	0.024***	0.036***	0.023***
	(7.70)	(10.98)	(7.55)
General	0.245		
	(1.25)		
Treatment	0.096		
	(0.44)		
Care	-1.593***		
	(-4.72)		
Information	-0.350		
	(-0.93)		
Accommodation	1.375***		
	(8.23)		
Composite SQ score		0.002	0.011***
		(1.01)	(4.12)
Patient characteristics	No	No	Yes
Hospital characteristics	No	No	Yes
Observations	248,063	248,063	248,063

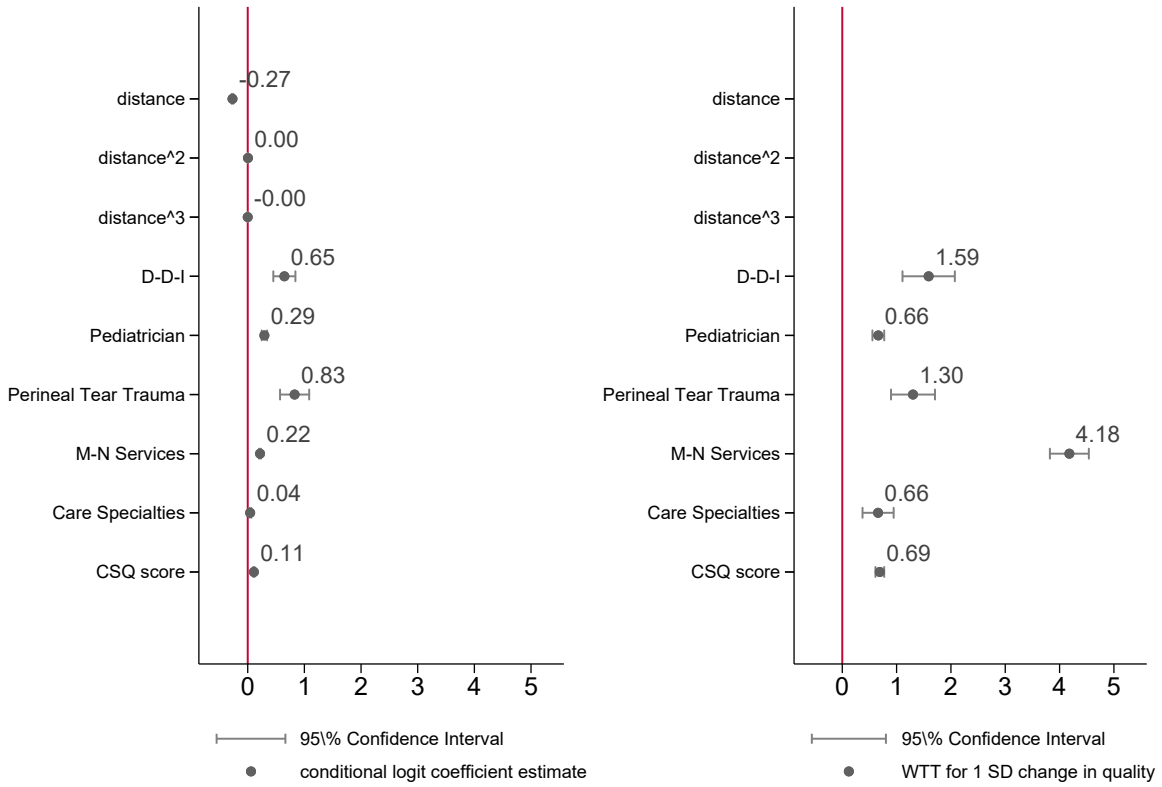
Note.— Table presents linear probability model on binary outcome whether a patient chose the closest hospital. Hospital characteristics include ownership type, beds, if-university, if-teaching, # of midwives; Department characteristics include Busyness indicator (# of cases per doctor); doctors' specialization levels (# of specialized doctors per # of all doctors); # of nurses specialized to take care of children - children nurses and dummies for missing quality indicators. Composite SQ score based on 5 satisfaction variables: General, Treatment, Care, Communication, Accommodation. Other hospital characteristics (all not significant at 10% level): number of beds, birth-staff ratio, share of specialized physicians. The model additionally controls for all choice-set averages, dummies for missing hospital characteristics, age, if emergency dummy. Standard errors are clustered on choice-set level. t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.
Conditional logit estimates for the choice of hospital

	(1)	(2)
Distance	-0.270***	-0.269***
	(-38.77)	(-38.63)
Distance^2	0.004***	0.004***
	(12.88)	(12.83)
Distance^3	-0.000***	-0.000***
	(-7.82)	(-7.82)
D-D-I	0.637***	0.647***
	(6.37)	(6.49)
Pediatrician	0.246***	0.294***
	(10.21)	(11.99)
Perineal Tear Trauma	0.585***	0.828***
	(4.38)	(6.31)
M-N-Services	0.224***	0.217***
	(24.52)	(23.74)
Care Specialties	0.031***	0.043***
	(3.36)	(4.54)
General	9.046***	
	(18.40)	
Treatment	-2.747***	
	(-5.07)	
Care	-5.605***	
	(-6.27)	
Information	0.977	
	(1.14)	
Accommodation	-0.673	
	(-1.57)	
Composite SQ score		0.109***
		(17.18)
Patient characteristics	Yes	Yes
Hospital characteristics	Yes	Yes
Observations	248,063	248,063

Note.— Table presents conditional logit model on patient choice of hospital (given 10 choices). The model additionally controls for hospital characteristics (ownership type, beds, if-university, if-teaching, # of midwives) and department characteristics (Busyness indicator (# of cases per doctor); doctors' specialization levels (# of specialized doctors per # of all doctors); # of nurses specialized to take care of children - children nurses) and dummies for missing quality indicators, for missing hospital characteristics. Composite SQ score based on 5 satisfaction variables: General, Treatment, Care, Communication, Accommodation. t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE 8.
Point and WTT estimates from the conditional logit model



NOTE.—Graphs presents the estimation results from the conditional logit model. The left panel indicates the coefficients and its confidence levels, while the right panel shows the WTT and its confidence levels.

Appendix A Additional tables and figures

Table A.1.
Classification of Elixhauser Comorbidities

Variable	Comorbidity
el1	Congestive heart failure
el2	Cardiac arrhythmias
el3	Vascular disease
el4	Pulmonary circulation disorders
el5	Peripheral vascular disorders
el6	Hypertension, uncomplicated
el7	Hypertension, complicated
el8	Paralysis
el9	Other neurological disorders
el10	Chronic pulmonary disease
el11	Diabetes, uncomplicated
el12	Diabetes, complicated
el13	Hypothyroidism
el14	Renal failure
el15	Liver disease
el16	Peptic ulcer disease (excluding bleeding)
el17	AIDS/HIV
el18	Lymphoma
el19	Metastatic cancer
el20	Solid tumor without metastasis
el21	Rheumatoid arthritis/collagen vascular diseases
el22	Coagulopathy
el23	Obesity
el24	Weight loss
el25	Fluid and electrolyte disorders
el26	Blood loss anemia
el27	Deficiency anemia
el28	Alcohol abuse
el29	Drug abuse
el30	Psychoses
el31	Depression

Note.— Detailed classification of Elixhauser Comorbidities with respective ICD-9 and ICD-10 codes can be found in Quan *et al.* (2005).

Table A.2.

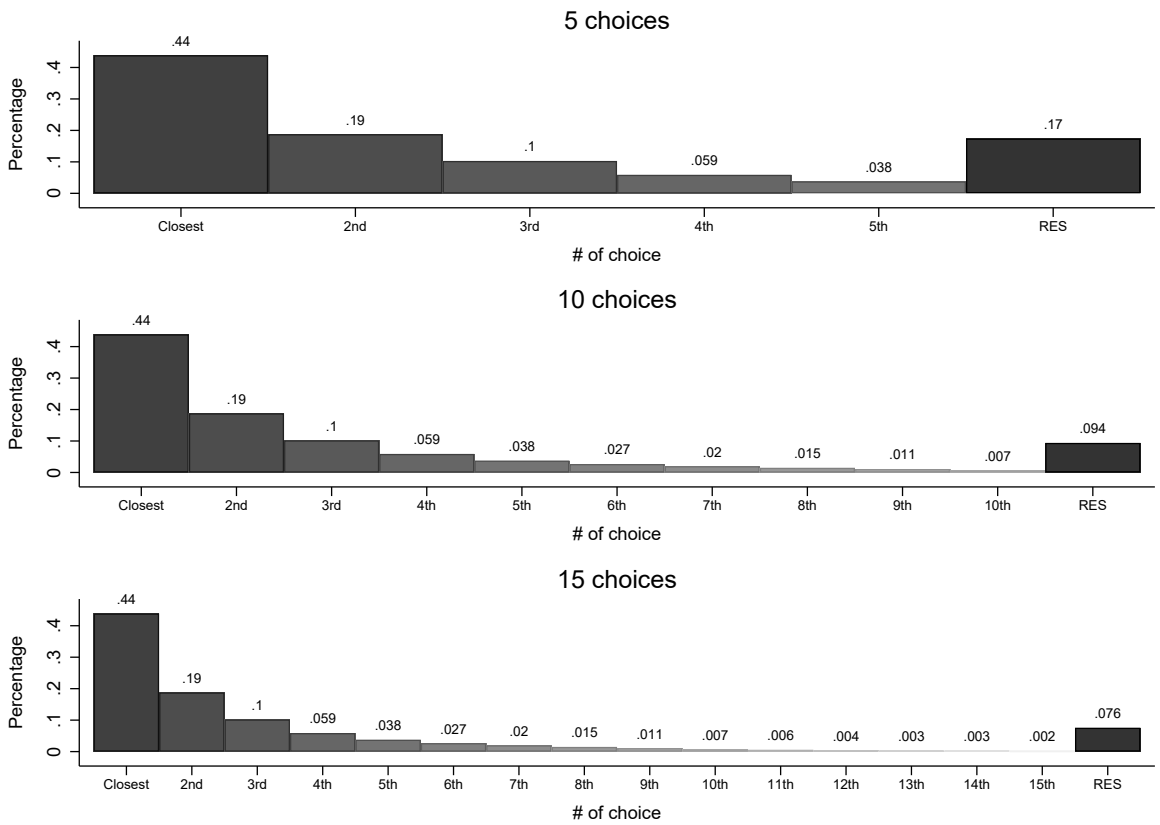
Linear probability model for the choice of the closest hospital. Alternative specification

	Passed each		Passed all group	
	1	2	3	4
Distance	-0.257***	-0.269***	-0.227***	-0.270***
	(-36.18)	(-38.60)	(-37.73)	(-38.41)
Distance^2	0.004***	0.004***	0.002***	0.003***
	(12.14)	(12.78)	(10.56)	(12.81)
Distance^3	-0.000***	-0.000***	-0.000***	-0.000***
	(-7.47)	(-7.76)	(-5.35)	(-7.83)
D-D-I$^D_{passed}$	0.128***	-0.020		
	(5.18)	(-0.79)		
Pediatrician$^D_{passed}$	0.319***	0.189***		
	(16.84)	(10.26)		
Perineal Tear Trauma$^D_{passed}$	0.563***	0.650***		
	(6.88)	(7.60)		
M-N Services	0.219***	0.215***		
	(23.13)	(23.45)		
Care Specialties	0.175***	0.039***		
	(17.37)	(4.10)		
Composite SQ score	0.041***	0.110***	0.039***	0.118***
	(7.04)	(17.20)	(6.90)	(18.55)
Legal Quality Assurance			0.287***	0.164***
			(19.22)	(11.24)
Treatment-relevant Equipment			0.193***	0.125***
			(36.47)	(23.58)
Patient characteristics	No	Yes	No	Yes
Hospital characteristics	No	Yes	No	Yes
Choice set characteristics	No	Yes	No	Yes
Observations	248,063	248,063	248,063	248,063

Note.— Table presents conditional logit model on patient choice of hospital (given 10 choices). Each quality indicator represents whether a patient passed required criteria (dummy). M-N Services is a score of medical and nursing services provided out of 5, Care Specialties - a score of care specialization out of 6. Legal Quality Assurance is a score of D-D-I, Paediatrician and Perineal Tear Trauma (out of 3). Treatment Relevant Equipment - a score of M-N Services and Care Specialties (out of 11); * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1.

Shares of choices by hospitals ranked by distance from patient residence



Note.—Graphs show percentages of sampled patients who chose the closest, 2nd closest, etc. hospital. "RES" is the residual category - share of people who did not chose within 5/10/15 closest hospitals.

Table A.3.

Conditional logit estimates for the choice of hospital by choice set size and distance definition

	5 choices		10 choices		15 choices	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance	-0.260***		-0.269***		-0.254***	
	(-25.00)		(-38.63)		(-39.42)	
Distance^2	0.004***		0.004***		0.003***	
	(7.59)		(12.83)		(10.89)	
Distance^3	-0.000***		-0.000***		-0.000***	
	(-4.07)		(-7.82)		(-5.66)	
Travel time		-0.244***		-0.250***		-0.248***
		(-22.19)		(-37.15)		(-46.63)
Travel time^2		0.002***		0.002***		0.001***
		(4.39)		(7.31)		(8.66)
Travel time^3		-0.000		-0.000**		-0.000**
		(-1.91)		(-3.07)		(-2.75)
D-D-I	0.522***	0.478***	0.647***	0.653***	0.662***	0.659***
	(4.54)	(4.37)	(6.49)	(6.28)	(6.57)	(6.69)
Pediatrician	0.244***	0.224***	0.294***	0.279***	0.303***	0.288***
	(8.33)	(7.62)	(11.99)	(11.48)	(12.87)	(12.48)
Perineal Tear Trauma	0.896***	0.820***	0.828***	0.827***	0.843***	0.805***
	(5.64)	(5.11)	(6.31)	(6.32)	(6.63)	(6.43)
M-N Services	0.226***	0.220***	0.217***	0.213***	0.214***	0.208***
	(21.07)	(19.47)	(23.74)	(22.74)	(24.24)	(23.74)
Care Specialties	0.031**	0.040**	0.043***	0.049***	0.044***	0.0528***
	(2.81)	(3.04)	(4.54)	(4.98)	(4.90)	(5.76)
Composite SQ score	0.088***	0.088***	0.109***	0.105***	0.117***	0.113***
	(10.91)	(10.80)	(17.18)	(16.08)	(19.20)	(18.58)
Observations	226,047	226,047	248,063	248,063	253,170	253,170

Note.—Table presents conditional logit model on patient choice of hospital. Heterogeneity is explored using different specifications and different samples. Columns (1) and (2) uses the sample with 5 choices, columns (3) and (4) - 10 choices and columns (5) and (6) - 15 choices. We present two differently generated samples, the first column of each choice model always represents choices by distance (km), while the second column - by travel time(min). The model additionally controls for hospital characteristics (ownership type, beds, if-university, if-teaching, # of midwives) and department characteristics (Busyness indicator (# of cases per doctor); doctors' specialization levels (# of specialized doctors per # of all doctors); # of nurses specialized to take care of children - children nurses) and dummies for missing quality indicators, for missing hospital characteristics. Composite SQ score based on 5 satisfaction variables: General, Treatment, Care, Communication, Accommodation. t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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