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Should I wait or should I go?
Travelling versus waiting for better healthcare

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Abstract

We study patient mobility in the Italian National Health System, using patient-episode level data on elective Percutaneous Transluminal Coronary Angioplasty procedures over the years 2008-2011. We examine how patients' choice of the hospital is affected by changes in waiting times and clinical quality within hospitals over time. We estimate mixed-logit specifications and show the importance of jointly controlling for time-invariant and time varying clinical quality to identify the effect of waiting times. Conversely, failure to capture variations in clinical quality over time does not affect the estimate of the discouraging effect of travel distance. We provide evidence that patients are responsive to changes in waiting times and clinical quality: average demand elasticity with respect to own waiting times and mortality is estimated to be – 0.17 and – 1.38, respectively. Patients' personal characteristics significantly influence how they trade off distance and waiting times with quality of care. We find a higher Willigness-To-Wait and Willingness-to-Travel to seek higher quality care for patients in the younger age groups and who are more severely ill. The results convey important policy implications for highly regulated healthcare markets.

Key words: patients' mobility; hospital choice; travel distance; waiting times; healthcare quality; mixed logit models.

JEL codes: I11, I18, R22

1. Introduction

Timely access to, and quality of, hospital services are central concerns for patients and regulators (e.g., Beckert et al, 2012; Gravelle et al, 2014; Gaynor et al, 2016; Gutacker et al, 2016). However, assessing the determinants of patient choice is challenging due to the multidimensional nature of quality and to the limited observability of important attributes. This notwithstanding, there is a growing interest in understanding how patients' mobility responds to variations in waiting times and clinical quality, as this offers key insights on patients' preferences.

Two waves of initiatives have boosted the relevance of these issues in public health systems: the enhancement of patient choice and the effort for shortening waiting times. Patient empowerment reflects the belief that greater choice can spur public organisations by promoting better quality and higher social welfare (e.g., Cookson and Dawson, 2012). Alongside with waiting times acting as a rationing device, long waits for care have become a major policy concern (Siciliani et al, 2014).

However, there are also reasons for scepticism about patients' ability to exercise an active choice when equity-oriented policies hinder competition, and common quality standards level out differences across providers, leaving patients with little incentive to bypass the nearest facility. Thus, it remains an empirical matter to determine whether patient choice is affected by preferences over factors other than geographical proximity, and to estimate the trade-off between hospital attributes (Balia et al, 2020).

We study patients' mobility in the Italian National Health Service (NHS) where secondary care is free of charge and patients' costs stem mainly from travel distance and waiting times. Hospitals retain incentives to attract patients, as they receive reimbursement through a Diagnosis Related Group (DRG)-based Prospective Payment System (PPS) (Lippi Bruni and Mammi, 2017; Cappellari et al, 2016). We analyse hospital choice in response to changes in waiting times and clinical quality within hospitals over time by using patient-level data on elective Percutaneous Transluminal Coronary Angioplasty (PTCA) for the period 2008-2011. Clinical quality is measured by mortality for Acute Myocardial Infarction (AMI), which is the key time-varying quality measure in our analysis (Berta et al, 2016; Moscelli et al, 2018).

We contribute to the literature on patient mobility and hospital choice by investigating the joint influence of hospital geographical accessibility, waiting times and clinical quality. Isolating the effect of distance and waiting times poses serious challenges because choice may reflect preferences for quality. If patients are sensitive to clinical quality, hospitals delivering better care will face higher demand, possibly inducing a positive correlation between waiting times and quality. Similarly, patients may be more or less discouraged by distance depending on perceived quality. Therefore, variations in hospital quality should be controlled for in order to obtain unbiased estimates of patients' Willingness-To-Wait (WTW) and Willingness-To-Travel (WTT).

We estimate conditional logit (CL) and mixed logit (ML) model specifications. We improve on existing studies on a number of issues. First, our estimation strategy jointly controls for time-invariant heterogeneity across providers via hospital fixed effects (FEs) and for time varying hospital quality. We show that failing to do so leads to biased estimates for the effect of waiting times. Conversely, in our study failure to account for variations in quality over time does not affect the estimate of the distance parameters. Notably, our findings lend support to the ML model, displaying preference heterogeneity for both unobserved and observed patient characteristics. Second, we investigate patients' preferences for a highly relevant speciality in the field of cardiology and in an institutional context where hospitals operate under weak competitive pressure, for which evidence on how patients trade off aspects of health care quality is still lacking. Third, we assess how the trade-off among hospital attributes vary with patients' characteristics. Detecting preference heterogeneity in terms of WTW and WTT for better quality and shorter waiting times is important for policy and helps target patients who are more at-risk of suffering from poor health care quality. Whereas some earlier studies looked at the trade-off between travel distance and hospital attributes such as waiting times and quality of care, to our knowledge we are the first to provide estimates of patients' WTW for higher quality. Policy makers may be interested in the extent to which longer waits may discourage patients from demanding higher quality care.

Our preferred specification yields an average elasticity of demand with respect to own waiting times of – 0.17, suggesting that a 1% increase in average waiting times (0.16 days) leads to a decline in the predicted number of admissions by around 0.17%. With respect to own quality, the average elasticity of demand is equal to – 1.38, so that a 1% increase in mortality rate (10% of the sample average) reduces demand by around 1.4%. The marginal rate of substitution between hospital attributes provides further insights. On average, patients are willing to travel an extra distance of about 1.4

kilometers for a 1-week reduction in waiting times. We find relatively little variation in the trade-off between waiting times and distance among different types of patients, with the reference patient having a WTT for a 1-week reduction in waiting times equal to about 2 kilometers. By contrast, patients' sensitivity to quality varies largely across patient characteristics, with younger groups and those more severely ill being more willing to trade off quality with distance and waiting times.

2. Background and motivation

2.1 Institutional setting

The Italian NHS is funded out of general taxation and provides universal coverage. Secondary care is largely supplied by public hospitals, either run by Local Health Authorities (*Aziende Sanitarie Locali*, ASLs) or operating as public Trusts (*Aziende Ospedaliere*, AOs), with administrative autonomy, extensively paid under PPS.[1] Primary care is organised as a list-based system and citizens are registered with a General Practitioner (GP). When referred by their GP or by a specialist, patients can access any publicly funded hospital. Since patients are not charged at the point of use, travel distance, waiting times and quality of care are the key drivers of hospital choice.

[1] Accredited private hospitals generally play only a minor role (Fattore et al, 2013). In Emilia-Romagna acute care beds covered by accredited private hospitals amount to 12%.

In the Italian NHS regions benefit from a large autonomy in organising and funding their health system (Di Novi et al, 2019).[2] Regions like Lombardy have encouraged competition within the public sector, as well as between public and accredited private centres (Moscone et al, 2012). On the contrary, in Emilia-Romagna policy-makers have favoured cooperation and coordination among providers by centrally planning production capacity, and by promoting a strong integration between hospital- and district-level services (Ferré et al, 2014). Located in the North-East of Italy, with a population of nearly 4.5 million people, the healthcare system of Emilia-Romagna can be broadly compared in terms of size, standards of services and underlying socio-economic conditions to the NHS-based systems of small and medium western European countries. Moreover, Emilia-Romagna is among the five Italian regions serving as benchmark to assess the health needs and the standard costs used to identify the basket of services covered by the NHS ("Essential Levels of Care"), giving national prominence to this regional context (Verzulli et al, 2017).

2.2. Related literature

Our work relates to two partially overlapping strands of literature: the studies on patient mobility and those that estimate demand elasticity to own waiting times. Hospital choice for elective care is inherently linked to patient mobility.[3] Earlier works have studied the influence of patients' and providers' characteristics on the propensity to seek treatment at hospitals other than the closest one (e.g. Tai et al,

[2] Such feature has also induced the economic literature on the Italian NHS to concentrate on single-region studies taking advantage of a homogenous institutional setting (e.g. Martini et al, 2014; Amaral-Garcia et al, 2015; Lippi Bruni et al, 2016; Perucca et al, 2019, Barili et al, 2021).

[3] See Brekke et al (2014) for a review of the hospital choice literature, and Aggarwal et al (2017) for a survey on patient mobility.

2004; Varkevisser and van der Geest, 2007; Robertson and Burge, 2011). Focusing on the Italian case, more recent contributions have investigated patients' migrations across jurisdictions by examining the push and pull factors and the financial consequences of patients seeking care out of their catchment area (e.g. Fabbri and Robone, 2010; Balia et al, 2014, 2018, 2020; Berta et al, 2021).

Hospital choice models typically rely on a multinomial logit specification, with patients choosing a provider within a set of possible destinations. The bulk of this literature uses cross-sectional data, and measures quality by means of clinical indicators such as mortality and readmission rates (Beckert et al, 2012; Varkevisser et al, 2012; Berta et al, 2016; McConnell et al, 2016). However, such variables may be correlated with unobserved hospital attributes affecting patient behaviour. By contrast, other contributions use a longitudinal design with hospital fixed effects, thus controlling for unobserved time-invariant heterogeneity across hospitals (e.g. Hodking, 1996; Tay, 2003; Gaynor et al, 2016; Gutacker et al, 2016; Moscelli et al, 2016; Avdic et al, 2019).

Demand response to waiting times has attracted considerable attention as well. A body of literature has used aggregate data at the ward and practice level (e.g. Martin and Smith, 2003; Gravelle et al, 2002), or has focused on small areas (Gravelle et al, 2003). Although with some variability, these studies have consistently outlined a negative and significant elasticity to waiting times, with estimates in most cases ranging between – 0.2 and – 0.3. As for Italy, Riganti et al (2017) find a demand elasticity to waiting times for surgical treatments between – 0.15 to – 0.24.

Even though individual-level information helps avoid the "ecological" fallacy when indicators capture effects that do not occur at the individual level (Martin and Smith, 1999), it has seldom been exploited to analyse the elasticity of demand for waiting times, as we do here. Moreover, patient-level data allows controlling for individual characteristics including hospital proximity, which improves estimate precision and makes it possible to analyse the trade-off between distance and waiting times (Pope, 2009). We account for preference heterogeneity for hospital characteristics, by interacting hospital attributes with patient characteristics and allowing preferences to vary randomly across patients.

2.3 Our contribution

The works closest to ours are Sivey (2012) and Moscelli et al (2016). The first uses patient-level panel data to study the impact of waiting times for cataract patients from English GP practices. It applies a multinomial logit framework and controls for quality differences via hospital FEs. The paper shows that, while waiting times positively affect choice before controlling for hospital time-invariant heterogeneity, the impact comes out negative once hospital FEs are included. The second contribution uses a panel of English hospitals to study how local market conditions – measured by the number of local rivals – affect demand elasticity for hip replacements, once quality of care, waiting times and distance are accounted for.

We differ from these contributions on a number of issues. First, we consider cardiovascular interventions where mortality rates are higher compared to cataract surgeries and hip replacements: a feature expected to affect WTT and WTW for higher quality of care. Second, identification in Sivey (2012) relies on the assumption that hospital quality does not vary over time, therefore excluding time-varying quality indicators: a restriction that is overcome in our context. In Moscelli et al (2016), the dynamics of the hospital market do not allow to control for unobserved characteristics at the level of single hospital, but only for homogeneous groups of providers. By contrast, we use a balanced sample of providers and include hospital FEs to account for time-invariant unobserved heterogeneity possibly associated with quality.

A further distinguishing feature of our work is the stability of the regulatory framework, which has always allowed free patient mobility (Levaggi and Zanola, 2004). This minimizes confounders due to providers' reactions to changes in the competitive environment. When patients are given greater choice opportunities, providers are incentivised to improve their attractiveness. Hence, when greater choice is introduced it may be hard to separate demand- from supply-side effects (Gaynor et al, 2016). Moreover, here providers are encouraged to co-operate rather than to compete, and the system is committed to ensure equity through regulated quality standards.

Finally, we assess how the trade-off among hospital attributes vary with patients' characteristics. Detecting preference heterogeneity in terms of WTT and WTW for better quality is important for policy, as it may help target patients who are more at-risk of suffering from poor quality services. While the former issue has attracted some attention, the latter has remained largely unexplored so far. Quite interestingly, we find a fairly steep gradient associated to changes both in severity conditions and patients' age. When the number of comorbidities increases, patients appear more willing to wait to gain access to a better performing centre, other things equal. On the contrary, ageing per se pushes patients in the opposite direction, with older individuals being more prone to obtain a quick access to treatment rather than to wait longer for being admitted in higher quality hospitals.

3. Methods

We estimate responsiveness to travel distance, waiting times, and clinical quality using patient-level data for elective PTCA surgeries. We rely on the multinomial logit framework (McFadden, 1974), and model utility of patient i conditional on choosing hospital j at time t as:

$$U_{ijt} = V_{ijt} + \nu_{ijt} \tag{1}$$

where V_{ijt} is the deterministic component and ν_{ijt} is the random error term. Alternative assumptions on the error structure and on the coefficients lead to different model specifications. We estimate conditional logit (CL) and mixed logit (ML) models. In the CL, the stochastic components of the conditional utility function in (1) are identically, independently distributed (iid) and follow a type-1 extreme value distribution. The deterministic component of utility is:

$$V_{ijt} = \beta_{di} f(D_{ij}) + \beta_{wi} W_{jt-1} + \beta_{qi} g(Q_{jt-1}) + \xi_j \tag{2}$$

where D_{ij} is the distance of patient i from hospital j, f is a cubic function of D_{ij}, W_{jt-1} denotes the median waiting time for an elective PTCA at hospital j in year $t-1$, Q_{jt-1} is the quality at hospital j in year $t-1$, and g is a quadratic function of Q_{jt-1}. ξ_j is a vector of hospital-specific FEs. The vector of coefficients on distance, waiting times and quality of care (β_{di}, β_{wi} and β_{qi}) are allowed to vary with patient characteristics so as to account for variation in preferences. Following previous studies, we assume that hospital choice responds to past, rather than current, waiting times and quality (e.g. Gutacker et al, 2016; Varkevisser et al, 2012). Lagged values prevent potential endogeneity due to the simultaneous influence of demand on waiting times and quality.

Hospital FEs absorb differences in persistent hospital characteristics, including, among others, teaching status, size, or whether a hospital provides highly specialized services, reputation and experience effects. Hospital FEs are crucial for identifying the impact of waiting times, as they control for unobserved time-invariant hospital attributes possibly correlated with waiting times. The coefficient is identified by the relationship between waiting times and hospital choice within hospitals over time: a negative coefficient implies that, on average, hospitals whose waiting times increased between $t-1$ and t decreased demand in period t, *ceteris paribus*.

The CL model relies on the Independence from Irrelevant Alternatives (IIA) property. Under this restrictive assumption, discrimination by patients among hospitals consists of pairwise comparisons unaffected by characteristics other than the pair under consideration. To overcome this limitation, we use the ML model, derived from the conditional utility function in (1) where ν_{ijt} are iid extreme values. The deterministic component of utility is the same as for the CL, except that the ML coefficients are allowed to vary randomly between individuals. By specifying individual random coefficients, the ML model accounts for unobserved preference heterogeneity and is robust to violations of the IIA (Train, 2009).

4. Data

Our primary data source is the hospital discharge dataset (*Schede di Dimissione Ospedaliera*, SDO) that contains individual-level information for patients receiving NHS-funded care in Emilia-Romagna. We study intra-regional patient mobility for elective admissions.[4] In doing so, we focus on short-distance movements of patients, while excluding long distance travels. Policy concerns for short-distance mobility largely prevail over those for the long-distance one, since the latter is relatively less frequent, in most cases involving highly complex procedures or idiosyncratic circumstances. On the contrary, the former can be induced by horizontal competition between nearby jurisdictions spurred by quality differences in local hospital markets: it involves larger groups of patients, with major implications for efficiency in resource allocation within the system, including the risk of unnecessary duplication of services.[5]

[4] We consider elective patients who reside in Emilia-Romagna. Non-elective (urgent) patients are excluded, as they are not placed on waiting lists. Residents treated in other regions are not included in our data, as these procedures are recorded in the datasets of destination regions. We also exclude residents from other regions treated in Emilia-Romagna, as their choice set should comprise the hospitals in the region of origin that do not appear in our dataset. Moreover, institutional barriers between regional health systems may affect the use of hospital services making the two groups of patients highly heterogeneous (Atella et al, 2014).

[5] The available evidence shows that inter-regional and intra-regional patient mobility in the Italian NHS are distinct phenomena influenced by different push and pull factors (e.g., Balia et al, 2020,

Our sample includes 15,766 patients undergoing elective PTCAs over the years 2008-2011, and each patient's choice set is assumed to embrace all publicly financed hospitals providing PTCAs. It comprises 22 hospitals in each year. On average, hospitals treat about 324 patients per year. The average number of patients treated by hospitals decreases from 344 to 266 between 2008 and 2011.[6] Figure 1 presents hospitals' location and volumes of activity.

[Figure 1 about here]

Waiting time is measured as the difference in number of days between the date when the patient is placed on the waiting list and the date of hospital admission. It has to be computed for each hospital in the choice set. However, while the waiting time at the chosen hospital is observed, the time a patient would have waited had he chosen an alternative provider is unknown. To tackle this problem, we follow Sivey (2012) in computing waiting times at the hospital-year level as the median of the individual waiting times for all elective PTCAs discharged at each hospital in each year.[7]

Clinical quality is measured by risk-adjusted mortality rates for AMI within 30 days of admission provided at hospital-year level by the Italian Ministry of Health through the National Outcome Evaluation Program (Programma Nazionale Esiti, PNE). The

2018). Different determinants of patients' willingness-to-travel for care for short- and long-distance movements, as well as varying DRG tariffs between intra- and extra-regional patients, contribute to explain such findings.

[6] Our model specification includes 22 alternative specific parameters corresponding to the regional hospitals that provide PTCAs, but no patient FEs. This feature ensures that, given our sample size, the estimator is free from the incidental parameter problem, which may affect non-linear models when the time dimension is short (s.c. small T) and the number of individual FEs increases with sample size (Lancaster, 2000).

[7] Median waits allow to account for the right skewed distribution of waiting times.

PNE releases procedure-specific indicators for all NHS hospitals for selected conditions and surgical interventions. These measures are computed linking clinical and administrative datasets, using rigorous scientific standards and validation procedures based on risk-adjustment mechanisms.

The PNE indicators were not disclosed to the public during the observational period and, therefore, the choice of the hospital cannot be attributed to the patient's direct assessment of the performance indicator of reference. In our analysis, the PNE measure acts as a proxy for quality retrieved by patients from various sources, including GP and specialist advices, as well as previous personal experience and positive word-of-mouth (e.g. Moscone et al, 2012; Gutacker et al, 2016). Such broad quality dimension is influenced by the human and physical capital endowment of each hospital and by the effort to deliver effective treatments (Gaynor and Town, 2012). In turn, these features are assumed to influence performances measured by indicators issued by the PNE.

Empirical research pointed out the existence of statistically significant correlations between patients' overall rating of the hospital and measures based on technical quality (Castle et al, 2005; Isaac et al, 2010). As for the context of our study, patients' surveys conducted in Emilia-Romagna revealed that physicians' recommendations are one of the most important determinants of their hospital choice (Fiorentini et al, 1999) and indicators for technical quality, such as risk-adjusted mortality rates, can be effectively used as proxies of patients' perceptions on more general quality dimensions.

Travel distance is computed (in kilometres) using Microsoft MapPoint, as the fastest road line route from the centroid of the patient's municipality of residence to each hospital site. Patient characteristics include age, gender, foreign citizenship and the Charlson Comorbidity Index (CCI). To account for underserved areas, we add a dummy taking value 1 if there is only one hospital providing PTCAs in the patient's LHA of residence, and 0 otherwise.

Since our dataset do not include individual-level proxies for socio-economic status, that has been shown to be relevant for hospital choice (e.g. Moscelli et al, 2018), we construct income-classes at the municipality level. Using data on average gross income from the Ministry of Economy and Finance, we construct dummy variables for each tertile of the income distribution, and attribute to each patient the income class corresponding to the municipality of residence.

Table 1 provides summary statistics. The average hospital has a median waiting time of 16 days and has risk-adjusted mortality rates equal to 9.9. Patients travel 18.6 kilometres on average for an elective PTCA, about three times the average distance to the nearest hospital, suggesting that choice is not uniquely driven by the purpose of minimising travel distance. Patients are on average 69 years old with a CCI of 1.028, men prevail over women and foreigners are less than 2%.

5. Results

Tables 2-3 present the results from the CL and the ML models, estimated using the `clogit` and `mixlogit` commands in `Stata 16` (Hole, 2007a). The first three columns consider specifications where additional sets of regressors are successively included. The most parsimonious one (column 1) controls for distance and waiting times only, allowing for observed preference heterogeneity through interactions with patient characteristics. Then, we include hospital FEs (column 2). In our preferred specification as illustrated in equation (2), we add the risk-adjusted mortality rate (column 3). Lastly, we replicate the final specification without interactions to provide average estimates for the whole sample of patients (column 4). All models (1)-(4) also include squared and cubic distance terms and the squared term of AMI mortality accounting for non-linear effects of distance and quality.[8]

5.1 Conditional logit estimates

Since the related literature mainly exploits a CL specification, we report the corresponding estimates in Table 2 for comparability purposes.

[Table 2 about here]

However, such specification relies on the IIA hypothesis, which is not supported in our data according to the Hausmann-McFadden test. Hence, we refer to the discussion of the ML specification for more detailed comments (section 5.2). It is worth noticing here that distance has always a negative and significant effect, confirming that patients prefer closer hospitals, *ceteris paribus*. Our measure of clinical quality has a negative and statistically significant effect. The coefficient for waiting times is

[8] We have also tested for non-linear effects of waiting times by adding the squared term. The results (available upon request) provide no evidence of non-linearities in the impact of waiting times on hospital choice. For this reason, the variable is entered in linear form.

positive and significant before including any control for quality (column 1). While it is no longer significant after accounting for time-invariant hospital differences through hospital FEs (column 2), the effect of waiting times becomes negative and significant once we control for clinical quality (column 3). Finally, the results of the ML without interactions (column 4) show that the distance, waiting times and quality coefficients are qualitatively similar to those obtained with the full set of interactions (column 3).

5.2 Mixed logit estimates

Table 3 shows the ML estimates, where the distance coefficients are allowed to vary across patients.[9] All remaining coefficients are assumed to be fixed as in the CL specification.[10] We fit the ML model by maximum simulated likelihood using 50 Halton draws.[11]

[Table 3 about here]

Results are similar to those obtained from the CL model, with the log-likelihood statistics and the information criteria (AIC, BIC) indicating that the ML model fits the

[9] As pointed out by previous studies, unobserved preference heterogeneity for distance might reflect the influence exerted by patients' family or friends (network effects), which can reduce the welfare loss associated with travelling for care (Balia et al, 2020).

[10] We have tested for the presence of unobserved heterogeneity with respect to waiting times and mortality rates. The results are reported in the Online External Appendix, and yield no evidence of significant unobserved heterogeneity with respect to neither waiting times or quality.

[11] We have tested the sensitivity of our findings in the final ML specification using up to 500 Halton draws. Even after increasing the number of draws by an order of ten, the estimated coefficients and the associated elasticities with respect to waiting times and quality are remarkably stable. The results for 500 Halton draws can be retrieved from the Online External Appendix.

data better.[12] Our preferred specification (column 3) shows that on average patients prefer closer hospitals, with shorter waiting times and lower mortality rates.

By comparing our findings across regressions (1)-(3), the coefficients are qualitatively similar except those for waiting times. While the effect of waiting times is positive and significant before controlling for any dimension of hospital quality, it is no longer significant once we include hospital FEs, and becomes negative and significant after accounting for time-varying hospital quality. Such evidence suggests that omitting to control for either source of differences in quality would deliver biased estimates of waiting time elasticity.

The interactions between hospital attributes and patient characteristics point to preference heterogeneity associated to observable personal characteristics. On the whole, age differences across patients emerge as a key driver of preferences over hospital attributes. In line with prior research, older patients appear more reluctant to travel (e.g., Beckert et al, 2012; Gutacker et al, 2016). These individuals more frequently suffer from limited mobility which hinders their access to distant providers. We also find that older people are less sensitive to variations in hospital mortality rates, suggesting that they are less responsive to quality differences or have poorer access to information on quality. In addition, they show a greater dislike for longer waiting times. A higher marginal disutility of time spent on waiting lists for elective treatment is consistent with shorter life expectancy, but it may also reflect severe conditions other than those captured by the number of comorbidities that call

[12] Consistently with previous evidence, we find that the mean ML coefficients are larger than the fixed coefficients in the CL model, implying that a large share of the variance in unobserved utility is given by the random parameters (e.g., Revelt and Train, 1998).

for timely intervention. Sicker patients appear more willing to trade off distance and waiting times for quality: they are more prone to travel and to wait for care and more likely to choose high quality providers. In addition, patients living in areas with only one hospital performing PTCAs are less reluctant to travel, less willing to wait and more responsive to variations in clinical quality. Finally, patients residing in more income-deprived areas are more reluctant to travel and less sensitive to changes in waiting times and quality.[13]

6. Size of the effect of waiting times and quality of care on hospital choice

We estimate the elasticity of demand of hospital *j* with respect to own waiting times as the % change in the predicted probability of choosing hospital *j* associated with a 1% increase in own waiting times. To compute the predicted probabilities, we use the `mixlpred` command in Stata following our preferred ML specification based on Equation (2). We then calculate the mean of the % change in the predicted probabilities across all hospitals to provide the average % change in the expected demand (i.e., predicted number of patients) resulting from a 1% increase in own waiting times. Similarly, we derive the own quality demand elasticity of hospital *j* as the % change in the predicted probability of choosing hospital *j* associated with a 1% decrease in own mortality rates.[14]

[13] While our data on patients' socio-economic status are aggregated at municipality level, future research should also consider the use of patient-level information to more precisely assess the impact of patients' socio-economic status on their responsiveness to waiting times and quality.
[14] Unfortunately, this approach does not provide standard errors. While in principle the bootstrap procedure could be used as an alternative to obtain standard errors, it is usually not operational in

Table 4 provides the means and standard deviations (SD) of the estimated demand elasticities. The results show a mean waiting time elasticity equal to - 0.17, suggesting that a 1% increase in average waiting times (0.16 days) leads to a decrease in the predicted number of admissions by around 0.17%. With respect to own quality, the elasticity of demand is equal to – 1.38, so that a 1% increase in mortality rate (10% of the sample average) reduces demand by around 1.4%.

[Table 4 about here]

Further insights into how the estimated marginal utilities of distance, waiting times and quality vary with patient characteristics are provided in Table 5. We use the delta method to provide standard errors (Hole, 2007b). The first column of Panel A displays the estimated marginal utilities obtained from the ML without interactions. The second column reports the marginal utilities derived from the ML with interactions for the reference patient, defined as the individual with average or modal characteristics (male, aged 69 years, Italian, with a CCI equal to 1.028, residing in the least income-deprived municipalities). In the successive columns we consider different "patient-types", whose characteristics varies each at a time, while keeping all other attributes at the level set for the reference patient. The exercise is performed for: females, patients at the 10th and 90th percentiles of the age and CCI distribution.

[Table 5 about here]

practice due to the massive computational burden needed to estimate the ML model. Because of that, bootstrap procedures are typically not implemented following ML estimation.

The most notable differences between the ML with and without interactions emerge for the quality attribute, with marginal utility varying largely across types of patients, whereas smaller differences are detected for the marginal utilities of distance and waiting times. Gender does not have a major impact on preferences, as women are only slightly less sensitive to variations in distance, waiting times and quality. On the contrary, age differences substantially affect sensitivity to quality, while leading to smaller changes in responsiveness to geographical proximity and waiting times. Patients at the 10th percentile of the age distribution (55 years) are less reluctant to travel and to wait for care compared to patients at the 90th percentile (89 years) and are also considerably more sensitive to improvements in quality. As for severity, patients with a CCI score equal to 6 (90th decile) are keener to wait and to travel farther than the average patient and display a larger marginal utility of quality.

The marginal rates of substitution between hospital attributes provide further insights. Based on the coefficient estimates obtained in the ML without interactions, the first row and column of Panel B gives the ratio of the marginal utility of waiting times over the marginal utility of distance. Such ratio can be interpreted as WTT for shorter waiting times, the additional distance that on average patients would be willing to travel for a reduction in waiting times by 1 day. According to our estimates on average patients are willing to travel about 1.4 kilometres for a 1-week reduction in waiting times. Similarly, the second row and first column of Panel B provides the WTT for higher quality. We find that on average patients are willing to travel about 0.12 kilometres for being treated in a hospital that ensures a 1% reduction in AMI mortality. The remaining columns of Panel B illustrate the WTT based on the ML estimates with the full set of interactions. The results for the reference patient point to a higher WTT for a 1-week reduction in waiting times, equal to 2 kilometres, and a larger WTT for a 1% decrease in hospital mortality, equal to 0.8 kilometres. While individual differences in the trade-off between distance and waiting times are relatively small, the trade-off between distance and quality varies substantially across types of patients. Patients with more comorbidities appear more willing to travel farther for higher quality, a result that supports the assumption made in earlier studies (Gowrisankaran and Town, 1999) and that is in line with previous evidence finding that patients who are more severely ill care more about quality (Gaynor et al, 2006). Interestingly, younger patients are more willing to travel to seek higher quality care, other things equal, suggesting that they are more prone to screen hospital destinations and less influenced by the discouraging effect of distance.

Additionally, we examine the trade-off between waiting times and quality, referred to as WTW for better quality. In the first column of Panel C, we show that on average patients are willing to wait about 0.6 days for a reduction in hospital mortality rate by 1%. The results in columns (2)-(7) obtained in the ML with interactions reveal a large variation in WTW across patients, with the most willing to wait for higher quality being younger patients and those suffering from more severe conditions. For the reference patient the results indicate a WTW of about 2.6 days for opting for a hospital where mortality decreases by 1%.

7. Robustness analyses

7.1 Restricted hospital choice sets

Since patients can choose any publicly financed provider, in our main analysis we have defined the choice set to include all 22 regional hospitals providing PTCAs. However, it may also be the case that patients consider only the subset of alternatives that are geographically closer. To test the robustness of our findings, we present here ML estimates based on the hypothesis that patients consider only the closest alternatives. In line with previous studies, we restrict the potential destinations to the 10-closest hospitals (Howard, 2005; Sivey, 2012). Even though the choice set of each patient is more than halved, in our data the risk of disregarding relevant destinations is negligible, since 99% of the actual choices fall within that range.

In Table 6, we present the ML estimates using the 10-closest providers criterion. These findings can be directly compared to those of Table 3. For the sake of brevity, we do not show the coefficients for the full set of interactions and concentrate on waiting times, distance and quality measures.

[Tables 6 about here]

As for waiting times, the inclusion of hospital fixed-effects and of time-varying quality indicators leads to the same pattern shown when the patient's choice set consists of the full set of regional hospitals. Moreover, also the magnitude of the coefficients of main policy interest (distance, waiting time and hospital quality) appears largely unaffected by the adoption of a different definition of the choice set.

For further insights, we present in the appendix the analysis where the choice set is defined according to a pre-set distance range, including hospitals located within 50 km from patient's residence, which corresponds to around 1-hour travel-time (Varkevisser et al, 2014). Overall, the results show that the estimated parameters are fairly robust also to this alternative definition of the patient choice set.

7.2 Extra-regional patient mobility

Due to lack of individual information on patients travelling to other regions, our analysis considers intra-regional mobility only, and the parameters capture the drivers of short- and medium-distance patients' movements. However, some short distance movements may not be recorded in our data, as some individuals may choose hospitals just across the regional border. To identify the areas of the region characterised by non-negligible cross-border outflows, we exploit aggregate data for the DRGs that count for 80% of all elective admissions included in our sample This information is available at the LHA-level and suggests that cross border mobility concentrates in the LHAs of Piacenza and Parma. In most other cases, the share of patients treated outside regional borders - including long-distance movements - ranges between 3-5%.

To test the robustness of our findings, we estimate our final ML specification excluding patients who reside in areas where outflows are non-negligible. In the remaining areas, we can confidently argue that the parameter estimates should not be affected by patients' outflows as the latter represent only a minor empirical issue. The results are reported in Table 7.

[Table 7 about here]

We consider exclusion criteria based on administrative and geographical grounds. First, we exclude residents in the LHA of Piacenza alone, and then residents in the LHAs of Piacenza and Parma together (first and second column of Table 7, respectively). The geomorphic configuration of the region also suggests an alternative criterion based on the exclusion of municipalities located on the northern border of the region. Emilia-Romagna is characterised by high hills and mountains in the south-western part that is scarcely populated, with relatively poor transport infrastructures and limited mobility. On the contrary, the northern part is characterised by a flat territory, more densely populated and well connected through efficient transport networks. This points to the largest share of outflows being due to patients residing close to the northern border and being directed toward northern regions (Lombardy and Veneto), where the quality of health service is deemed to be as high as in Emilia-Romagna. Based on these considerations, we exclude patients residing in the municipalities located in the northern border of the region, irrespectively of the LHA they belong to (third column of Table 7). We find that restricting the analysis to geographical areas where patient outflows are a minor issue leaves the estimates largely unchanged. Such evidence is reassuring that our main findings are not driven by missing information on residents treated in different regions.

7.3 Additional indicators of hospital quality

A possible limitation of the analysis is that it makes reference to a single indicator and thus it may not capture the multidimensional nature of (time-varying) quality. In order to broaden the scope of the study, we have considered a richer set of measures as proxies for quality dimensions that can be credibly retrieved by patients through their sources of information (family networks, GPs, etc.) and that, at the same time, are validated at the scientific and institutional level.

In the Appendix, we present and discuss in more detail the empirical findings that stem from the inclusion of additional PNE indicators relating to the cardiovascular area. Overall, these proxies for quality do not influence the probability that a patient chooses a destination once differences in 30-day AMI mortality rate across providers are controlled for: the latter indicator emerges as a good summary measure for quality dimensions that are relevant for patient choice. Most importantly, the coefficients of main policy interest are largely unaffected.

8. Discussion and conclusion

As in Italy public hospital care is free of charge, patients trade off travel distance versus waiting times and clinical quality when choosing their destination for elective procedures. We estimated patient choice models to assess demand responsiveness to changes in waiting times and quality of care by using patient-level data on elective PTCA surgeries. A major challenge when studying mobility towards hospitals with shorter waiting times is the potential correlation with quality. Thanks to disease-specific quality indicators issued by public authorities and to a balanced panel of hospitals, we are able to control for time-invariant quality (via the hospital FEs) and for the time varying aspects of clinical quality (via risk-adjusted mortality rates for AMI). In this way, we can relax assumptions that may not hold in every context, such as constant quality over time or uniform quality patterns within groups of hospitals, which were present in previous studies.

Our results documented the importance of jointly accounting for time-invariant differences across hospitals and time-varying clinical quality. Omitting time-varying quality controls produces biased estimates of responsiveness to waiting times, while no impact is recorded on the propensity to travel for care. We found that waiting times have a negative and significant impact on hospital demand, with the estimated average elasticity of demand for waiting times being – 0.17, and that on average patients are willing to travel an extra distance of about 1.4 kilometers for shortening waiting times for care by 1-week. There is relatively little variation in the trade-off between waiting times and distance across different types of patients, with the reference patient having a WTT for a 1-week reduction in waiting times equal to 2 kilometers. We also highlighted that patients respond to variations in hospital mortality rates over time, and estimated the average demand elasticity to mortality rates to be – 1.38. Responsiveness to changes in hospital quality varies widely across patient characteristics, with younger age groups and those more severely ill being more willing to trade off quality with distance and waiting times.

Waiting times have a negative and significant effect on demand. This has important implications for highly regulated healthcare systems. A relevant concern in such contexts is whether increasing NHS resources is an effective policy instrument to reduce waiting times. However, the interplay between demand- and supply-side factors in determining waiting times suggests that increasing public funding may not always result in a reduction in waiting times (e.g., Siciliani and Iversen, 2012), as increasing NHS capacity may bring forward previously latent demand. Small demand elasticity with respect to waiting times as shown in our study suggest that patients' response to a reduction in waiting time is relatively small on average. Net of this effect, increasing healthcare resources is expected to shorten waiting times.

Finally, our finding that hospital choice is affected by changes in clinical quality suggests that favouring well-informed patient choice - e.g., by disclosing information on hospital quality to the public - may produce beneficial effects also in highly regulated settings. We have shown that, even in such contexts, patients' sensitivity to quality changes makes hospitals with better health outcomes more attractive. At the same time, policy-makers should carefully monitor the consequences in terms of access to high quality care for those patients who are unlikely to bypass local providers.

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The study, based on routine administrative information, was carried out in compliance with Emilia-Romagna Regional Authority data processing regulations and the Italian Data Protection Act. Administrative data were anonymized prior to the analysis at the regional statistical office, where each patient is assigned a unique identifier. This identifier does not allow to trace the patient's identity and other sensitive information.

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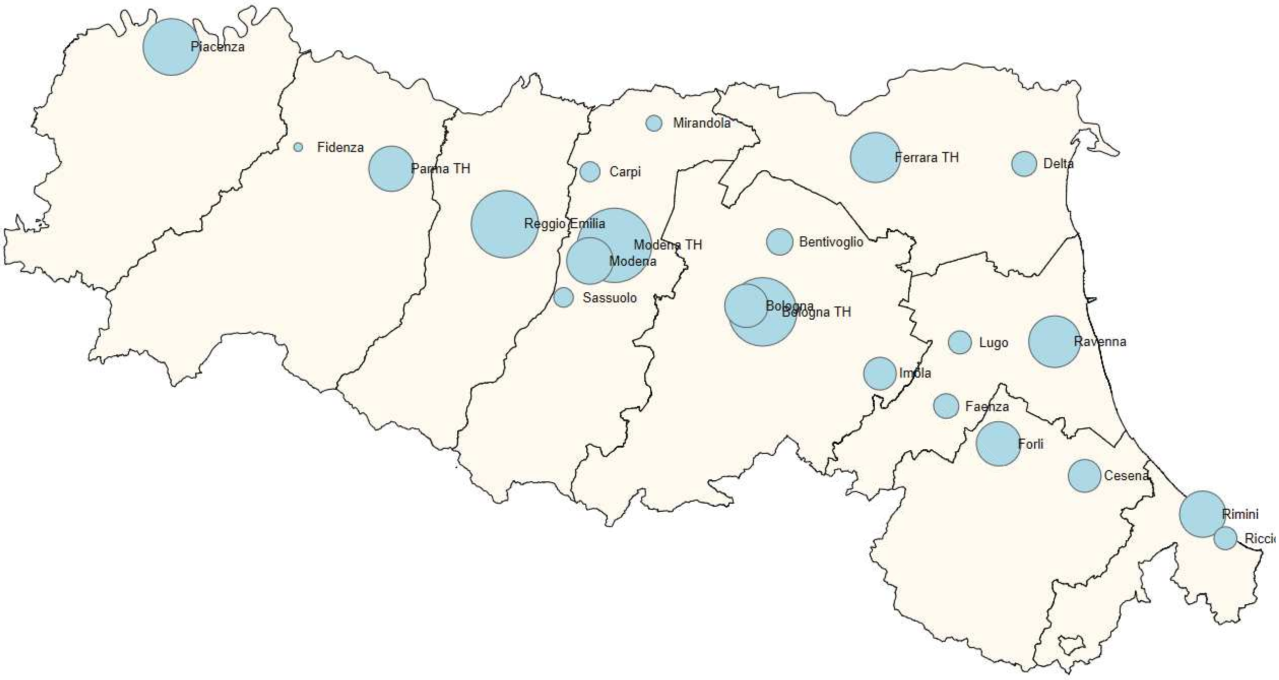
Figure 1. Emilia-Romagna region, map of hospital locations.



Note: Circle size is proportional to the volume of elective PTCA treatments provided in each hospital. TH, teaching hospital.

Table 1. Descriptive statistics: years 2008-2011.

Variable	Mean	SD
Hospital characteristics		
Median annual inpatient waiting time (days)	16.148	*9.379*
Between-hospital variation		*8.162*
Within-hospital variation		*4.862*
AMI Mortality rate (%)	9.923	*2.563*
Between-hospital variation		*1.856*
Within-hospital variation		*1.799*
Patient characteristics		
Distance to hospital visited (km)	18.612	*19.119*
Distance to closest hospital (km)	6.457	*6.436*
Female	0.263	*0.440*
Age	69.017	*11.440*
Foreigner	0.017	*0.130*
Charlson comorbidity index (CCI)	1.028	*1.419*
Unique provider within the LHA of residence	0.316	*0.465*
Income deprivation – group 1 (more deprived)	0.328	*0.470*
Income deprivation – group 2	0.332	*0.471*
Income deprivation – group 3 (least deprived)	0.339	*0.473*
Sample characteristics		
No. of hospitals	22	
No. of patients	15,766	

AMI, Acute Myocardial Infarction. LHA, Local Health Authority. SD, Standard Deviation.

Table 2. Results from conditional logit estimation of hospital choice.

Variable	Model 1	Model 2	Model 3	Model 4
Distance (in km)	-0.142***	-0.128***	-0.122***	-0.154***
	(0.0113)	*(0.0132)*	*(0.0132)*	*(0.00262)*
Distance^2 (/100)	0.148***	0.159***	0.151***	0.0728***
	(0.0182)	*(0.0212)*	*(0.0212)*	*(0.00413)*
Distance^3 (/10000)	-0.0456***	-0.0572***	-0.0543***	-0.0130***
	(0.00759)	*(0.00921)*	*(0.00919)*	*(0.00164)*
Waiting time	0.0464***	0.00323	-0.0274***	-0.0268***
	(0.00748)	*(0.00975)*	*(0.0106)*	*(0.00293)*
AMI mortality rate			0.535**	0.311***
			(0.238)	*(0.0538)*
AMI mortality rate^2			-0.0415***	-0.0166***
			(0.0120)	*(0.00266)*
Interactions with distance	Y	Y	Y	N
Interactions with distance^2	Y	Y	Y	N
Interactions with distance^3	Y	Y	Y	N
Interactions with waiting time	Y	Y	Y	N
Interactions with AMI mortality	N	N	Y	N
Interactions with AMI mortality rate^2	N	N	Y	N
Hospital FEs	N	Y	Y	Y
Log-likelihood	-16600.0	-12503.7	-12,383.2	-12912.4
AIC	33,264.0	25,113.5	24,904.4	25878.7
BIC	33,608.2	25,683.6	25,646.6	26169.1

AMI, Acute Myocardial Infarction.
Notes: Estimates from the conditional logit model. Years 2008-2011. All hospital-specific indicators are lagged by one year. No. of observations = 346,852. No. of patients = 15,766. No. of hospitals = 22. Standard errors in parentheses. Significance levels: ***p< 0.01, **p< 0.05, *p< 0.1.

Table 3. Results from mixed logit estimation of hospital choice.

Variable	Model 1	Model 2	Model 3	Model 4
Distance (in km)	-0.154***	-0.132***	-0.126***	-0.164***
	(0.0138)	*(0.0168)*	*(0.0168)*	*(0.00338)*
Distance^2 (/100)	0.146***	0.125***	0.117***	0.0230***
	(0.0242)	*(0.0290)*	*(0.0292)*	*(0.00717)*
Distance^3 (/10000)	-0.0640***	-0.0659***	-0.0625***	-0.0125***
	(0.0111)	*(0.0130)*	*(0.0132)*	*(0.00321)*
Waiting time	0.0520***	0.00795	-0.0241**	-0.0312***
	(0.00789)	*(0.0107)*	*(0.0119)*	*(0.00323)*
AMI mortality rate			0.458*	0.397***
			(0.257)	*(0.0612)*
AMI mortality rate^2			-0.0380***	-0.0210***
			(0.0129)	*(0.00301)*
Interactions with distance				
Age	-0.0000281	-0.000357	-0.000371	
	(0.000194)	*(0.000231)*	*(0.000233)*	
Female	0.0206***	0.0203***	0.0192***	
	(0.00486)	*(0.00659)*	*(0.00655)*	
Foreigner	-0.0123	-0.0133	-0.0161	
	(0.0158)	*(0.0182)*	*(0.0191)*	
CCI	0.00598***	0.00596***	0.00611***	
	(0.00145)	*(0.00199)*	*(0.00197)*	
Unique local provider	-0.0543***	-0.0229***	-0.0205***	
	(0.00495)	*(0.00728)*	*(0.00734)*	
Income - 1st tertile	0.0892***	-0.00790	-0.0123	
	(0.00630)	*(0.00848)*	*(0.00842)*	
Income - 2nd tertile	0.0496***	-0.0307***	-0.0356***	
	(0.00609)	*(0.00855)*	*(0.00857)*	
Interactions with distance^2				
Age	-0.00169***	-0.00164***	-0.00160***	
	(0.000325)	*(0.000373)*	*(0.000381)*	
Female	-0.0156*	-0.0106	-0.00956	
	(0.00809)	(0.0116)	*(0.0115)*	
Foreigner	0.000264	-0.00234	0.00227	
	(0.0252)	*(0.0277)*	*(0.0300)*	
CCI	-0.00161	0.000191	-0.0000952	
	(0.00233)	*(0.00346)*	*(0.00340)*	

Table 3. (*continued*).

Variable	Model 1	Model 2	Model 3	Model 4
Unique local provider	0.0699***	0.0332***	0.0307***	
	(0.00770)	*(0.0112)*	*(0.0114)*	
Income - 1st tertile	-0.0867***	0.00815	0.0142	
	(0.0109)	*(0.0139)*	*(0.0137)*	
Income - 2nd tertile	-0.0492***	0.0552***	0.0633***	
	(0.0126)	*(0.0174)*	*(0.0175)*	
Interactions with distance[3]				
Age	0.000761***	0.000845***	0.000824***	
	(0.000142)	*(0.000163)*	*(0.000169)*	
Female	0.00360	-0.000185	-0.000444	
	(0.00322)	*(0.00513)*	*(0.00505)*	
Foreigner	0.00713	0.0115	0.00964	
	(0.00957)	*(0.0104)*	*(0.0120)*	
CCI	-0.000495	-0.00176	-0.00160	
	(0.000889)	*(0.00157)*	*(0.00153)*	
Unique local provider	-0.0206***	-0.00910**	-0.00832*	
	(0.00289)	*(0.00450)*	*(0.00459)*	
Income - 1st tertile	0.0208***	-0.00234	-0.00433	
	(0.00449)	*(0.00570)*	*(0.00554)*	
Income - 2nd tertile	0.00789	-0.0314***	-0.0348***	
	(0.00605)	*(0.00892)*	*(0.00903)*	
Interactions with waiting time				
Age	-0.000304***	-0.000689***	-0.000315**	
	(0.000110)	*(0.000146)*	*(0.000161)*	
Female	0.00548*	0.00978**	0.0104**	
	(0.00301)	*(0.00401)*	*(0.00444)*	
Foreigner	0.000654	-0.00769	-0.0156	
	(0.0108)	*(0.0142)*	*(0.0156)*	
CCI	0.00365***	0.00524***	0.00421***	
	(0.000899)	*(0.00122)*	*(0.00136)*	
Unique local provider	-0.0794***	-0.0628***	-0.0445***	
	(0.00344)	*(0.00534)*	*(0.00586)*	
Income - 1st tertile	-0.00636*	0.0108**	0.0172***	
	(0.00355)	*(0.00502)*	*(0.00563)*	
Income - 2nd tertile	0.0153***	0.0116**	0.0171***	
	(0.00385)	*(0.00533)*	*(0.00606)*	

Table 3. (*continued*).

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Interactions with AMI mortality				
Age			-0.00361	
			(0.00356)	
Female			0.0675	
			(0.100)	
Foreigner			0.522	
			(0.370)	
CCI			0.0887***	
			(0.0322)	
Unique local provider			-0.637***	
			(0.116)	
Income - 1st tertile			0.422***	
			(0.111)	
Income - 2nd tertile			0.303***	
			(0.116)	
Interactions with AMI mortality rate^2				
Age			0.000319*	
			(0.000179)	
Female			-0.00282	
			(0.00497)	
Foreigner			-0.0297	
			(0.0186)	
CCI			-0.00460***	
			(0.00159)	
Unique local provider			0.0375***	
			(0.00576)	
Income - 1st tertile			-0.0180***	
			(0.00553)	
Income - 2nd tertile			-0.0126**	
			(0.00579)	
SD of Distance			0.0536***	0.0601***
			(0.00257)	*(0.00237)*
SD of Distance^2			0.00803***	-0.00732***
			(0.00161)	*(0.00240)*
SD of Distance^3			-0.00198**	-0.000388
			(0.000986)	*(0.000726)*

Table 3. (*continued*).

Variable	Model 1	Model 2	Model 3	Model 4
Hospital FEs	N	Y	Y	Y
Log-likelihood	-16,443.0	-12,290.8	-12,179.4	-12,533.0
AIC	32,956.1	24,693.6	24,502.9	25,126.1
BIC	33,332.6	25,296.0	25,277.3	25,448.8

AMI, Acute Myocardial Infarction.
Notes: Estimates obtained using the Stata mixlogit command (Hole, 2007a), 50 Halton draws. Years 2008-2011. All hospital specific indicators are lagged by one year. No. of hospitals = 22. No. of patients = 15,766. No. of observations = 346,852. Standard errors in italics. Significance levels: ***p< 0.01, **p< 0.05, *p< 0.1.

Table 4. Average elasticities of demand.

	Average elasticity of demand
Waiting time (days)	-0.17
	(0.139)
Mortality rate from AMI (%)	-1.38
	(1.292)

AMI, acute myocardial infarction.
Notes: Results based on the mixed logit regression in column 3 of Table 3. Standard deviations in parentheses.

Table 5. Marginal utility, WTT and WTW: main effects and effect by type of patient.

	Mixed logit without interactions	Mixed logit with interactions					
		Baseline	Female	Age = 55	Age = 89	CCI = 0	CCI = 6
Panel A: Marginal utility							
Distance (in km)	-0.157**	-0.144***	-0.128***	-0.131***	-0.161***	-0.150***	-0.114***
	(0.002)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.005)*	*(0.004)*	*(0.006)*
Waiting time (days)	-0.031***	-0.042***	-0.031***	-0.037***	-0.048***	-0.046***	-0.021**
	(0.003)	*(0.005)*	*(0.006)*	*(0.006)*	*(0.006)*	*(0.005)*	*(0.008)*
Mortality rate from AMI (%)	-0.019*	-0.110***	-0.098***	-0.148***	-0.055***	-0.107***	-0.122***
	(0.010)	*(0.017)*	*(0.020)*	*(0.019)*	*(0.021)*	*(0.018)*	*(0.029)*
Panel B: WTT							
Waiting time (days)	0.197***	0.292***	0.242***	0.282***	0.298***	0.306***	0.184**
	(0.021)	*(0.037)*	*(0.048)*	*(0.044)*	*(0.040)*	*(0.037)*	*(0.075)*
Mortality rate from AMI (%)	0.121*	0.764***	0.766***	1.129***	0.342***	0.713***	1.070***
	(0.066)	*(0.123)*	*(0.160)*	*(0.147)*	*(0.130)*	*(0.122)*	*(0.264)*
Panel C: WTW							
Mortality rate from AMI (%)	0.613*	2.619***	3.161***	4.000***	1.146***	2.326***	5.810**
	(0.330)	*(0.455)*	*(0.737)*	*(0.660)*	*(0.414)*	*(0.413)*	*(2.344)*

AMI, acute myocardial infarction. WTT, willingness to travel. WTW, willingness to wait.
Notes: ML without interactions: results based on the mixed logit regression in column 4 of Table 3. ML with interactions: results based on the mixed logit regression in column 3 of Table 3. Standard errors calculated using the delta method are reported in parentheses.

Table 6. Mixed logit model: choice set with the 10 nearest hospitals.

Variable	Model 1	Model 2	Model 3	Model 4
Distance (in km)	-0.156***	-0.167***	-0.164***	-0.166***
	(0.0212)	*(0.0258)*	*(0.0260)*	*(0.00471)*
Distance^2 (/100)	0.102*	0.160***	0.179***	0.0291***
	(0.0533)	*(0.0592)*	*(0.0609)*	*(0.0112)*
Distance^3 (/10000)	0.00773	-0.0550	-0.0761**	-0.0275**
	(0.0356)	*(0.0365)*	*(0.0384)*	*(0.0114)*
Waiting time	0.0467***	-0.00575	-0.0356***	-0.0314***
	(0.00831)	*(0.0115)*	*(0.0126)*	*(0.00327)*
AMI mortality rate			0.473*	0.415***
			(0.266)	*(0.0618)*
AMI mortality rate^2			-0.0380***	-0.0220***
			(0.0134)	*(0.00305)*
Interactions with distance	Y	Y	Y	N
Interactions with distance^2	Y	Y	Y	N
Interactions with distance^3	Y	Y	Y	N
Interactions with waiting time	Y	Y	Y	N
Interactions with AMI mortality	N	N	Y	N
Interactions with AMI mortality rate^2	N	N	Y	N
SD of Distance	0.0240***	0.0535***	-0.0432***	0.0543***
	(0.00498)	*(0.00281)*	*(0.00311)*	*(0.00364)*
SD of Distance^2	0.0424***	0.0104	0.0374***	0.0371***
	(0.00468)	*(0.00668)*	*(0.00387)*	*(0.00775)*
SD of Distance^3	-0.00691*	-0.00063	0.00650***	-0.00883**
	(0.00381)	*(0.00233)*	*(0.00231)*	*(0.00388)*
Hospital FEs	N	Y	Y	Y
Log-likelihood	-15564	-11526.1	-11,404.4	-11768.5
AIC	31198.1	23164.2	22,952.7	23597
BIC	31546.8	23722.1	23,670.0	23895.9

AMI, Acute Myocardial Infarction.
Notes: Estimates obtained using Stata `mixlogit` command (Hole, 2007)a), 50 Halton draws. All hospital-specific indicators are lagged by one year. No. of observations = 156,760. No. of patients = 15,676. No. of hospitals = 10. Standard errors are in parentheses. Significance levels: ***p< 0.01, **p< 0.05, *p< 0.1.

Table 7. Mixed logit model: sensitivity analyses using different sample sets.

Variable	(1)	(2)	(3)
Distance (in km)	-0.117***	-0.119***	-0.107***
	(0.0172)	*(0.0190)*	*(0.0162)*
Distance^2 (/100)	0.086***	0.0891**	0.0728***
	(0.0298)	*(0.0349)*	*(0.0271)*
Distance^3 (/10000)	-0.044***	-0.0473***	-0.0404***
	(0.0132)	*(0.0167)*	*(0.0116)*
Waiting time	-0.0274**	-0.0269**	-0.0209*
	(0.0121)	*(0.0128)*	*(0.0121)*
AMI mortality rate	0.4982*	0.487*	0.558**
	(0.2599)	*(0.262)*	*(0.265)*
AMI mortality rate^2	-0.0404***	-0.0399***	-0.0428***
	(0.0131)	*(0.0132)*	*(0.0133)*
Interactions with distance	Y	Y	Y
Interactions with distance^2	Y	Y	Y
Interactions with distance^3	Y	Y	Y
Interactions with waiting time	Y	Y	Y
Interactions with AMI mortality	Y	Y	Y
Interactions with AMI mortality rate^2	Y	Y	Y
SD of distance	0.056***	0.0580***	0.0550***
	(0.0026)	*(0.00288)*	*(0.00286)*
SD of distance2	-0.002	-0.000811	-0.000142
	(0.0019)	*(0.00227)*	*(0.00172)*
SD of distance3	0.0003	-0.000175	0.000243
	(0.0009)	*(0.00135)*	*(0.000722)*
Hospital FEs	Y	Y	Y
Log-likelihood	-11,886.6	-11428.1	-11516.9
AIC	23,917.2	23000.2	23177.9
BIC	24,685.6	23764.2	23946.4
No. of observations	318,560	299,882	319,066
No. of patients	14,480	13,631	14,503

AMI, Acute Myocardial Infarction.
Notes: Results based on the mixed logit regression in column 3 of Table 3 using different sample sets: (1) - sample excludes residents in the LHA of Piacenza; (2) - sample excludes residents in the LHAs of Piacenza and Parma; (3) - sample excludes residents in the Emilia-Romagna's northern border. All hospital-specific indicators are lagged by one year. Standard errors in parentheses. No. of hospitals = 22. Significance levels: ***p< 0.01, **p< 0.05, *p< 0.1.

Appendix

A.1 Restricted hospital choice sets

In this appendix, we complement the analysis developed in the main text, where we tested the robustness of our findings to a more restrictive definition of patients' choice set. Based on different conjectures about how patients process information, researchers have typically assumed that patients focus either on the closest destinations, or on hospitals within a given distance radius. While in section 7.1 we examined the implications of the *k*-closest providers criterion, we consider here patient choice sets that include all hospitals within a distance of 50 km, corresponding to 1-hour travel time on average (Varkevisser et al, 2014). Such criterion comprises around 94% of the destinations actually chosen.[15]

Table A.1 reports the estimates based on the latter criterion. The estimated parameters are similar to those of the models presented in Tables 3 and 6 in the main text.[16]

[Tables A.1 about here]

When considering hospitals within 50 km of distance from patient residence, the marginal utility from quality for the reference patient is – 0.113, while the full model provides an estimated value of -0.110 when all hospitals are included in the choice set and -0.112 when considering only the ten closest providers. With respect to distance

[15] The total number of observations used for the analysis is equal to 75,855 with the fixed radius criterion of 50 km, while it was 156,760 under the 10 closest providers criterion, and 346,852 when all 22 hospitals are included.
[16] The models presented in Table A1 include a quadratic function of distance. The cubic term for distance was excluded since it was never statistically significant.

and waiting times, the estimated marginal disutilities are – 0.138 and – 0.043, respectively. These values are very close to those obtained in the full specification for the entire set of hospitals (-0.144 and -0.042, respectively) as well as for the ten closest providers (-0.139 and -0.041, respectively). Not surprisingly, these figures translate into comparable values for WTT and WTW. The new evidence confirms that the empirical findings are robust to alternative definitions of the patient choice set.

A.2 Additional indicators of hospital quality

Since extending the spectrum of quality indicators included in the analysis may help account for features that a single measure may not capture, in this appendix we add further measures for (time-varying) hospital quality. As in the present study hospital quality acts as a magnet for patients' flows, we are interested in proxies for quality that can be accessed by patients and that are scientifically and institutionally validated. The PNE program serves this purpose well: it is promoted by National and Regional Health Authorities and it releases risk-adjusted indicators for different clinical areas. Thus, we restrict our attention to the PNE indicators for the cardiological area. In our main analysis, we have used 30-days AMI mortality rate as key time varying quality measure, an indicator that has gained a prominent position as a proxy for clinical quality of hospital services (e.g., Cooper et al, 2011; Bloom et al, 2015).

We assess here the robustness of our findings by considering a richer set of measures for clinical quality. The additional indicators meet the following criteria: they refer to the cardiovascular area, are risk-adjusted and available for the full set of hospitals included in our sample. Three PNE indicators meet these requirements: readmission rates after AMI, 30-day mortality rates for patients with heart failure and readmission rates for patients with heart failure.[17] In Table A.2, we report the estimates of our mixed logit specification corresponding to column 3 of Table 3, augmented by the three quality indicators discussed above.

[Tables A.2 about here]

According to our results, these measures for hospital quality do not seem to influence the probability that a patient chooses a particular destination once we control for differences in AMI mortality rates across providers, with the latter indicator emerging as a good summary measure for quality dimensions that are relevant for patient choice. Most importantly, our findings for the coefficients of main policy interest are largely unaffected.

[17] Ideally, it would have been advisable to include also quality indicators referring to elective procedures. Unfortunately, measures such as 30-day mortality rate for coronary bypass and for aortic valvuloplasty cannot be included in the present analysis. Due to the concentration of such procedures in a limited number of points of delivery, these indicators are released only for 6 out of the 22 hospitals of our sample.

Table A.1. Mixed logit model: choice set with all hospitals within 50 km from patient residence.

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Distance (in km)	-0.121***	-0.125***	-0.122***	-0.160***
	(0.0251)	*(0.0344)*	*(0.0340)*	*(0.00529)*
Distance^2 (/100)	-0.0308	-0.0249	-0.0147	0.0221**
	(0.0540)	*(0.0718)*	*(0.0710)*	*(0.0110)*
Waiting time	0.0410***	-0.0154	-0.0408***	-0.0315***
	(0.00965)	*(0.0135)*	*(0.0147)*	*(0.00337)*
AMI mortality rate			0.408	0.404***
			(0.298)	*(0.0634)*
AMI mortality rate^2			-0.0332**	-0.0214***
			(0.0150)	*(0.00314)*
Interactions with distance	Y	Y	Y	N
Interactions with distance^2	Y	Y	Y	N
Interactions with waiting time	Y	Y	Y	N
Interactions with AMI mortality	N	N	Y	N
Interactions with AMI mortality rate^2	N	N	Y	N
SD of Distance	-0.0151	0.0443***	0.0438***	0.0402***
	(0.00946)	*(0.00418)*	*(0.00425)*	*(0.00381)*
SD of Distance^2	-0.00644	0.00126	0.000401	0.00270
	(0.0223)	*(0.0126)*	*(0.0127)*	*(0.0146)*
Hospital FEs	N	Y	Y	Y
Log-likelihood	-12510.9	-8978.3	-8,876.6	-9090.8
AIC	25073.8	18050.6	17,879.3	18237.7
BIC	25313.9	18484.7	18,461.2	18496.3

AMI, Acute Myocardial Infarction.
Notes: Estimates obtained using Stata `mixlogit` command (Hole, 2007a), 50 Halton draws. All hospital-specific indicators are lagged by one year. No. of observations = 75,855. No. of patients = 14,794. No. of hospitals = 22. Standard errors are in parentheses. Significance levels: ***p< 0.01, **p< 0.05, *p< 0.1.

Table A.2. Mixed logit model: sensitivity analysis to the inclusion of other quality indicators

Variable	**Coeff.**
Distance (in km)	-0.110***
	(0.0166)
Distance^2 (/100)	0.0816***
	(0.0281)
Distance^3 (/10000)	-0.0461***
	(0.0121)
Waiting time	-0.0316**
	(0.0124)
AMI mortality rate	0.553**
	(0.262)
AMI mortality rate^2	-0.0426***
	(0.0132)
AMI readmission rate	0.00813
	(0.0182)
Heart failure mortality rate	-0.0260
	(0.0362)
Heart failure readmission rate	0.0673
	(0.0426)
Interactions with distance	Y
Interactions with distance^2	Y
Interactions with distance^3	Y
Interactions with waiting time	Y
Interactions with AMI mortality	Y
Interactions with AMI mortality rate^2	Y
Interactions with AMI readmission rate	Y
Interactions with heart failure mortality rate	Y
Interactions with heart failure readmission rate	Y
SD of Distance	-0.0540***
	(0.00263)
SD of Distance^2	0.00116
	(0.00207)
SD of Distance^3	0.00106*
	(0.000585)

AMI, Acute Myocardial Infarction.
Notes: Estimates obtained using the Stata `mixlogit` command (Hole, 2007a), 50 Halton draws. Years 2008-2011. All hospital specific indicators are lagged by one year. No. of hospitals = 22. No. of patients = 15,766. No. of observations = 341,471. Standard errors in italics. Significance levels: ***p< 0.01, **p< 0.05, *p< 0.1.