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Patient choice: two essays and a new statistical software package

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Contents

Chapter 1

Background

Prior literature has recognized the importance of shedding light on how patients choose their treating provider. The health care context analysed in this work is characterized by regulated price and asymmetric information. At the same time the quality of treatment is crucial for patient's welfare. In the last decades, national health care systems had tried to respond to necessity of maximizing quality of care by enacting policies focused on giving to the patient freedom to choose their preferred providers along with the disclosure of the quality information about hospitals. Indeed, it has been recognized by past literature that freedom of choice and availability of quality information improve quality of care and lead patients to discard low-quality hospitals. The literature, however, have neglected three crucial aspects of patient choice. First, all empirical contributions aimed to understand the mechanisms of patient choice by assuming that hospitals are perceived as similar organizations. However, a recent theoretical contribution hypothesized that patients differently value health care providers and might to tend to elect a "reference hospital" which they perceive as best quality (Levaggi and Levaggi, 2017). Second, earlier research has focused on procedures supplied in a hospital setting (inpatient) or on choice of general practitioners. The outpatient sector has been overlooked, even though it is important for patient welfare and for health cost containment through prevention and early treatment. Third, the largely used econometric specifications in the discrete choice setting are based on logit models and their generalizations. Besides, it begins to be recognized that patients may be influenced by their peers (Berta et al., 2016; Moscone, Tosetti, and Vittadini, 2012) when choosing hospitals or they might be affected also by mechanism be correlated at the spatial level. Although econometric theory has provided tools for performing discrete choice analysis in a spatial framework, the software to do so are still limited. The aim of this work is to fill the above mentioned gaps and they will be approached in the following way. This chapter identifies the extant literature in patient choice and his gaps. Subsequently, Part 2 is aimed to understand whether patients elect reference hospitals by using Italian Hospital Discharge Record Data in three regions and whether the perception of patients of a reference hospital varies between different organizational market approach. Part 3 is aimed at understanding the determinants of outpatient choice and to useful policy implications by simulating a relocation of a provider. Part 4 introduces a novel Stata package, which allows to perform spatial logit analysis.

1.1 Literature Review

1.1.1 Europe based research

Concerning European studies, a Dutch study (Varkevisser and Geest, 2007a) indicated that high waiting time and distance are strong predictors of patients bypassing the closest hospital. Sivey (2012) examined the trade-off between travel time and waiting time by estimating their elasticity of demand. He used a sample including 86,000 elective cataract patients from the Hospital Episodes Statistics (HES) from the UK National Health Service. Specifically, he use discrete choice models (conditional logit models and latent class multinomial logit) including travel time, waiting time and hospital fixed effects, interacted with patient characteristics. In more detail, two aspects of waiting time were considered: the outpatient waiting time and the inpatient waiting time. The former is the time incurring between the general practitioner referral and the outpatient appointment while the latter is the time interval between the decision to admit the patient and the actual surgery date.

From the models he estimated waiting time and travel time elasticities by artificially increasing by 1% the measure of interest, re-estimating the model and measuring the variation of demand due to the change of the dependent variable. Remarkably, inpatient and outpatient waiting time elasticities are very similar and this yields that patient value the same equal amounts of time spent waiting for care, regardless the activity to be performed. Specifically, 1% increase in waiting time leads on average 0.1% decrease in hospital demand. Further, the estimated travel time elasticities of demand are estimated to range from 1.4 to 1.5, which are remarkably similar to what estimated in Varkevisser, Geest, and Schut (2010). Using data from the same country, Gaynor, Propper, and Seiler (2016) evaluated the impact of the removal of the constrains to patient choice occurred in 2006 on hospital competition and health outcomes. They estimated elasticity of demand for coronary artery bypass graft (CABG) with respect to quality and waiting time before and after the 2006 freedom of choice reform using quality, waiting time and distance as regressors. With the estimated model, they evidenced that removing the restrictions to patient choice increased patient responsiveness to quality changes but not to waiting times. Further, they report some heterogeneity in elasticity changes due to the referom; indeed, sicker patients were more sensitive.

In the Italian context (region Lombardy), Moscone, Tosetti, and Vittadini (2012) studied the impact of social interaction on patient choice of hospital and its relationship with the hospital quality. They hypothesized that, in contexts where information is limited , patient may seek for advice from their peers before choosing a provider. Their reserach aim was to investigate whether such information-gathering mechanism increased the probability of choosing a high quality hospital. They compared elective patient choices versus emergency patient choices, given that an individual needing emergency care is unlikely to consult her peers before being admitted to the hospital. Empirically, they built a "network effect" measure which represents the share of people with the same disease and living in the same municipality who have previously chosen the same hospital specified it into a choice model along with hospital characteristics and distance. The network effect variable was then interacted with a dichotomous variable which indicated elective patients in a similar approach to Differences in Differences. The hospital-specific coefficient attached to such interaction variable measured the degree of correlation between the patients' behavior and the behavior of their peers. In the second step, they fit a model with the aim to test the correlation between the strength of this network effect and hospital-specific quality indicators, namely readmission rates and mortality rates. In the first stage Moscone, Tosetti, and Vittadini (2012), found a positive and significant network effect among people living in the same municipality indicating that patients tend to seek advice from their neighbors while, in the second stage, they report that such information-gathering may lead patients to end up in lower quality hospitals. Another Italian paper (Berta et al., 2016) based on 2012 data from the same Italian region followed a two-stage empirical strategy. The first stage was concerned in estimating a mixed logit model to investigate the determinants of patient choice which gave further evidence of the network effects reported in Moscone, Tosetti, and Vittadini (2012). The second stage, used the predicted probabilities of the choice model to estimate competition indicators basing on the procedure of Kessler and McClellan (2000) to study the impact competition on adverse health outcomes and report that, all other factor being equal, there is no relationship between higher hospital competition and better mortality or readmission rates. The authors recognize the limitations of quality measures based on adverse events; however, they argue that asymmetric information due to the lack of availability of hospital rankings may not incentive hospitals to improve quality.

Further evidences from UK are reported in Beckert, Christensen, and Collyer (2012), which aimed to methodologically contribute to the literature on patient choice by using a demand model in order to simulate the effects of hospital mergers. Indeed, the central authority may decide to merge hospital in order to achieve economies of scope and scale. However, hospital mergers may decrease the quality of care through the reduction of competition. For this purpose, they used two conditional logit models on a sample of 37,000 hip replacement admissions occurred in 216 British hospitals in the period 2008-2009. Their empirical specification included distance, quality measures (CQC ratings and MRSA infections), waiting time and hospital attributes interacted with patients'characteristics. With their model, they estimate that patients are more sensitive to distance than to quality and waiting time. Furthermore, they shed light on the role of GPs in referring patients to hospitals. In particular, the probability that a patient chooses a hospital increase with the share of referrals that her GP had previously made to that hospital. In simulating mergers, Beckert, Christensen, and Collyer (2012) reported that the elasticity of hospital demand with respect to quality decreases. Specifically, the most dramatic decrease is reported in areas where hospital competition is lower. Varkevisser, Geest, and T.Schut (2012) considered data regarding angioplasty Dutch patients in 2006 to investigate the relationship between publicly available quality ratings (readmission rates and hospital rankings) and hospital choice through a mixed logit model. They report that a 1% decrease of readmission rates is associated to a 12 % demand increase. Moreover, a one-point increase of hospital reputation (13% with respect to the sample mean) corresponds to an increase of hospital demand of as much as 65%. However, their findings highlight that using unadjusted readmission rates as quality indicator may tempt hospitals to improve their measured quality by cream skimming, this effect is due to the fact that readmission rates and outcome-based quality measures are not adjusted for case-mix.

Moscelli et al. (2016) used HES data on all elective primary hip replacement admissions from 2002 to 2013 in order to deepen the understanding of hospital demand. Their main purposes were to evaluate the realtionship between distance, waiting time and quality on patient choice and to understand the impact of hospital competition on elasticity of demand. Their large panel allowed to explore how such dynamics change after the reform which introduced free hospital choice in 2006 in the UK. Empirically, they considered a conditional logit model including distance, waiting times and clinical quality indicators (one month emergency readmissions , one-year revision-rates and one month mortality rates). They further calculate demand elasticities and willingness to travel for quality. In keeping with the literature they report that distance is a strong determinant of patient choice. Further, their findings evidenced that quality is a driver of patient choice, especially after the 2006 reform. Indeed, providers with higher readmission rates were less likely to be chosen after 2006 while revision rates had no impact on patient choice and, finally, hospitals with higher mortality rates were less likely to be chosen throughout the entire period. However, their empirical model evidence that patients prefer to choose hospitals with shorter waiting times after 2008. Moscelli et al. (2016), did not find differences in marginal utilities for quality for urban and rural patients while marginal utility of distance had no significant time change but was higher for urban residents. In estimating elasticities, they reported that such measure decreased in absolute value after 2006, that patients are willing to travel 0.5 less kilometers to choose a provider with a one less standard deviation in emergency readmissions. Further, their contribution highlights that demand is more elastic with respect to own quality as the number of competitors increases.

In acknowledging the limitations quality measures based on reputation or mortality and readmission rates, Gutacker et al. (2016) investigate the role of different aspects of quality in explaining hospital demand for hip replacement. Specifically, they focus on pre-operative outcome measures (PROMs) which were introduced in the British National Health Service in 2009. PROMs are validated questionnaires which encompass patients' health status and health-related quality of life before and after treatment. These measures overcome the limitations of crude quality measures. Indeed, they are risk-adjusted and reflect patients' perceptions of changes in health status . For this purpose, they used data concerning primary 170,000 elective hip replacement performed in the UK from 2010 to 2013 along with PROM data and waiting times. The PROM questionnaire contained three instruments: the Oxford Hip Score (OHS), the EuroQoL-5D descriptive system and the EuroQol Visual Analogue Scale. In their model, they focused on the first as it is correlated with the other two and provides a hip replacement-specific measure. They used a random-utility model specification including the non-linear effect of distance, the OHS, waiting times and a set of hospital characteristics. Their models allowed variation in preferences related to their observed characteristics (conditional logit) and variations in patient's preferences due to unobserved characteristics (mixed-logit). In keeping with the literature, they observed that the reference patient tends to dislike traveling and to wait for care. Further, *ceteris paribus*, they report that patient are more likely to choose private providers and specialized providers than public or non-specialized hospitals. Concerning quality, Gutacker et al. (2016) show that patient demand is more responsive to measures which reflect the change in health condition (the OHS) due to treatment rather than to outcome-based measures (readmission rates and mortality rates). In their more conservative model specification, they report that one standard deviation increase of OHS is associated to an additional willingness to travel of 0.1 km while readmission rates or mortality rates are not significant, other factors beign equal. They conclude highlighting that hospitals may attract patients by enhancing the quality features which are directly experienced in the health status of patients. Further, they remark that market structure might be a factor determining incentives for quality competition; indeed, the ability of attract patients through quality improvement decreases rapidly with distance.

Santos, Gravelle, and Propper (2017) focused on investigating the role of quality in patients' choice of family doctor practices by analyzing the choices of more than 3 million adults residing in the UK. All individuals in the UK are allowed to choose a family doctor which is a medical professional who provide primary care and act as gatekeepers to non-emergency hospital care. They underlined that studying the impact of family doctor quality to patient choice is crucial from an economic perspective, because quality of primary care can avoid costlier use of hospital care by prevention of declines in patients' health status. In the UK, family doctors are free of charge to patients and are contracted to the National Health System with a mix of capitation and pay-for-performance payment schemes deriving from the Quality and Outcome Framework (QOF) indicators reflecting four dimensions of primary care quality: clinical, organizational, patient experience and additional services. Their main empirical specification is a conditional logit model including a lagged

QOF measure to set the causality direction between quality and choice, a polynomial expression of distances and general practice characteristics. They reported that patients are likely to avoid to travel further and to choose higher quality practices. Specifically, one standard deviation increase of the QOF score leads to an increase of 900 enrollees (17% of the average). Moreover, patients tend to prefer practices located in the same administrative area, which is interpreted as a non-linear distance effect reflecting natural boundaries or intrinsic connectivity characteristics. These results were confirmed by a mixed logit model which revealed little heterogeneity in preferences regarding quality and distance as well as a two-stage model instrumenting quality with the mean quality of all other practices in the same administrative area. Other stratified specifications underline that men preferences with respect to quality vary among age groups and genders. In evaluating the marginal rate of substitution, they evidenced that individuals residing in wealthier or more educated areas are characterized by be willing to exchange more time spent traveling for an additional unit of quality than the low-income and the less-educated. They conclude supporting the argument that enhancing choice in health system is an effective policy to promote quality of primary care.

Interestingly, Beukers, Kemp, and Varkevisser (2014) used a sample of 55,000 hip replacements performed between 2008 and 2010 on all Dutch hospitals to examine the relationship between patient choice and hospital and patient characteristics. Overall, their results suggest that patients prefer to undergo hip replacement in closer hospitals with short waiting time and with high quality ratings. Further, they report that there are gender and age-related heterogeneity in preferences with women rating preferring non-academic hospitals and older adults preferring to travel closer and to general hospital than the younger. Interestingly, their model revealed that there were changes in in the relationship between hospital quality ratings over the years.

1.1.2 US based research

In their seminal study, Kessler and McClellan (2000) investigated the impact of hospital competition on health outcomes and costs using data concerning urban Medicare enrollees hospitalized for a primary acute myocardial infarction (AMI) in 1985,1988,1991 and 1994. Indeed, in prior literature there were conflicting views on the welfare implications of competition in health care. Specifically, previous research had highlighted that competition may both reduce or increase costs prices as well as ambiguous findings on the changes in excess capacity. However, Kessler and McClellan (2000) recognized that earlier research, was limited in three fashions. First, the impact of competition due to free choice on health outcomes and costs was not directly investigated; ruling out the possibility of inferring conclusions on social welfare. Second, previous empirical literature had kept using biased measures of competition. On one hand, the specification of geographic market size as a function of actual patient choices and bed capacity lead to market sizes and competition measures that are depending on unobservable attributes of hospital quality and are the results of the competitive process. Further, specifying discrete market borders (i.e. assuming that hospitals can be either inside or outside a specific patient catchment area) yields to biased estimates of the effect of competition on hospital quality. Moreover, they argued that studying the impact of competition on health outcomes using indicators based on patient's actual choice may induce an endogeneity bias due to the correlation between competition and unobservable determinants of patients' costs and health status.

In order to overcome such methodological limitations they used a three-stage empirical approach. In the first step, they fit a hospital choice model with exogenous patients and hospital characteristics as covariates and unrestricted choice sets. In the second stage, they obtained "the weighted average of the competition indexes for hospitals expected to treat patients in a given geographic area of residence, weighted by the hospital's expected share of area patients" (Kessler and McClellan, 2000; p590) which are uncorrelated with unobserved patient characteristics. Third, such unbiased measures were used as regressors along with zip code and time fixed effects to estimate the effect of hospital competition on health outcomes and treatment intensity. They found that, overall, in markets where hospital competition was higher AMI patients had better health outcomes in terms of mortality and complications. Moreover, competition was associated to lower costs in 1990s even though in the 1980s had the opposite effect.

Tay (2003) used data on all Medicare enrollees who suffered from a heart attack. Concerning hospital competition, she considered the "medical arm race hypothesis": given that fully insured patients are insensitive to price hospitals are assumed to compete for skilled physicians who choose to work hospitals with high-tech equipment. In turn, hospitals buy costly equipment to be more attractive to physicians and their patients. Therefore, hospital competition is based on horizontal product differentiation (location) and on vertical product differentiation (quality). This differentiation implies that each hospital can be viewed as a provider of a unique location-quality product combination. Spatial differentiation of hospitals gives suppliers geographic market power, enabling lower-quality hospitals to attract patients. Empirically, Tay (2003) specified a conditional logit model using input-based measures (staff-per-patient, staff-per-bed) along with outcome-based quality indicators (mortality, complications rates and high-tech quality). In her work, Tay (2003) reports that quality and distance are the main drivers of hospital choice. Specifically, their trade-off varies with patient characteristics.

Similarly, Hodgkin (1996) used health outcomes for patients with cardiac conditions, evidenced that disclosing quality information had a significant impact on influencing patient's probability of choice and health outcomes. Similar results where reported by Howard (2006) using one-year graft failure rate following kidney transplantation, and Pope (2009) using hospital quality rankings for all Californian Medicare patients from 1998 to 2004 and a sample of other US hospitals from 1994 to 2002. However, even though quality public reporting leads patients to avoid poor performing or unrated surgeons Wang et al. (2011) recognize that distance plays a more important role using an eight-year panel (1998-2006) of 115,000 coronary artery bypass graft (CABG) occurred in Pennsylvania as well as surgeon ratings and hospital report cards.

1.1.3 Remarks

To summarize, the literature have highlighted that freedom of choice favors competition between hospitals and gives incentive to health care providers to improve quality of care and, thus, patient welfare. However, to exploit the benefits of hospitals competition the literature has recognized that quality information about quality must be publicly available. Indeed, in contexts where there is incomplete information about hospital quality the outcome of competition might be distorted leading to loss of patient welfare. In general, the literature have recognized that patients are unwilling to travel and to wait for treatment. The main findings of the current body of literature are reported in Table 1.1.3. With respect to the current body of knowledge, the gaps of which this thesis is focused on are:

1. the literature have widely investigated competition and patient choice in the hospital framework; however, the inpatient setting have been overlooked;

2. the current body of research assumes that hospitals are perceived as similar by patients. How-

ever, this not may be the case, indeed a recent theoretical work hypothesized that hospitals might be differently perceived by patients to the point that they elect a "reference hospital" which they perceive as best quality (Levaggi and Levaggi, 2017);

3. from a methodological point of view the literature have consolidated the use of choice models such as the conditional logit. However, preferences of patients might be spatially correlated. This aspect may have been neglected for the scarcity of software performing discrete choice analysis in the spatial econometrics framework.

Table 1.1: Main empirical contributions to patient choice literature

Contribution	Data	Methods	Results
Sivey (2012)	UK elective cataract patients (2001-2004)	CL, LCL	Patients are more responsive to variations in travel time than in waiting time
Moscone, Tosetti, and Vittadini (2012)	Region Lombardy patients (2004-2007)	Two stage: CL and OLS on hospital quality indicators	Patients tend to seek advice from their peers in choosing hospitals. However, this might lead to choose low quality hospitals
Gutacker et al. (2016)	Hip replacement UK patients (2010-2013)	CL, ML	Patients are more responsive to quality measures related to the change of their health condition rather than outcomes
Santos, Gravelle, and Propper (2017)	UK patients registered at general practices in 2010	CL, ML	Patients tend to choose higher quality general practices and to avoid to travel further. Heterogeneity in preferences
Berta et al. (2016)	Elective Patients from Lombardy (2012)	Three stage: ML and OLS	No relationship between competition and mortality rates. Lack of hospital rankings may not give incentive hospitals to improve quality
Varkevisser, Geest, and T.Schut (2012)	Angioplasty patients in the Netherlands in 2006	CL	Low readmission rates and high reputation make hospitals attractive to patients. Unadjusted readmission rates used as measure of quality may tempt hospitals to opt for cream-skimming strategies.
Moscelli et al. (2016)	Hip replacement data in UK (2002-2013)	CL	Patients based their choices on quality as measured by mortality. Patients avoid to travel further and to seek for treatment in hospitals with higher waiting times
Beukers, Kemp, and Varkevisser (2014)	Hip replacement patients in the Netherlands (2008-2010)	CL	patients prefer to undergo hip replacement in closer hospitals with short waiting time and with high quality ratings. Patient-related heterogeneity in preference over hospital attributes
Kessler and McClellan (2000)	AMI Medicare Patients 1985-1994 (US)	Three stage: CL and FE	AMI patients had better health outcomes in terms of mortality and complications in areas where competition was more intense
Gaynor, Propper, and Seiler (2016)	Elective UK CABG patients 2003-2007	OLS on aggregate hospital market share. Structural choice model including patient and physician preferences.	The removal of choice constraints results in increased patient responsiveness to quality changes; giving hospitals incentive to raise quality. The reform increased patient welfare, especially for the sickest and those with a lower income.
Beckert, Christensen, and Collyer (2012)	Hip replacement patients in UK. 2008-2009	CL. Merger simulation	Mergers (less competition) decrease the sensitivity of patients to quality changes especially in rural areas.
Tay (2003)	AMI Medicare patients	CL	Quality and distance are the main driver of patient demand
Pope (2009)	Medicare CABG patients (1994-2004)	FE, ML	The disclosure of quality information affected both patient choice and health outcomes

CL=conditional logit,FE=fixed effect regression, LCL=latent class logit, ML=mixed logit, OLS=ordinary least squares

Chapter 2

Do patients elect reference hospitals? Evidence from three Italian Regional Health Systems

This chapter is derived from the working paper "Patient choice and the reference hospital: evidence from Lombardy" in coauthorship with Rosella Levaggi and Gianmaria Martini presented at the AIES workshop 2017, at the Health Econometrics Workshop 2018 and at the NERI workshop 2019. I am responsible for all the changes in this chapter.

Abstract

We consider some recent theoretical contributions showing that an hospital may be perceived as a reference by patients, and gets a higher share than its local competitors. Hence, we study the possible effect of a reference hospital in patient choices, and whether there is on this dimension a prevalence of private or public hospitals. We estimate conditional logit models for hip-replacement admissions in Lombardy, Veneto and Emilia Romagna over the period 2013-2016. We find that in addition to typical determinants of patient choice (i.e., distance), being perceived as a reference hospital is an important factor affecting the probability of being chosen, but with an interesting variance across Regions, genders and education level.

2.1 Introduction

The reforms that have reshaped health care systems across European countries have introduced competition and enhanced patients choices. This is especially true for hospital provision that accounts for about 40% of the OECD countries' total health care spending (OECD, 2017). The expected benefits from competition are appealing for countries that face rapidly escalating health care costs, increasing dissatisfaction with the quality of care provided, and shrinking public resources. The theoretical literature assumes the existence of some form of spatial competition among providers and patients choice usually depends on the evaluation of quality and transport cost (Brekke, Siciliani, and Straume, 2012; Brekke, Siciliani, and Straume, 2010; Brekke, Siciliani, and Straume, 2011; Gaynor, Ho, and Town, 2015). In this context, the institutional settings plays a fundamental role.

Competition and patient choice has been intensively investigated in the empirical literature, usually for specific treatments and mostly with reference to US and UK . The effect of competition on quality is rather mixed. In general, it may enhance efficiency, but the pressure on hospital volumes may also make hospitals reduce their quality level (Moscelli, Gravelle, and Siciliani, 2019) and the ability of patients to actually make hospital compete may allow those with an outside option to get better quality (Dardanoni, Laudicella, and Li Donni, 2018). Both the theoretical and empirical literature assume that quality, although not verifiable, may be observed by the patients. While this assumption is a necessary condition for the existence of a competitive model, for hospital care what patients may perceive as quality is not so straightforward. Quality has several dimension that may be perceived and weighted differently across patients. This may of course change both the competition setting and the outcome of competition. Another interesting issue that the literature has not fully explored so far is the actual process that patients use to choose an hospital for elective care. Given that health care is a primary good, the question of how strong is the trade off between different quality dimensions (medical quality, hospitality quality and other measures) is quite relevant. For other goods and services the literature show that customers may choose their preferred product/brand by evaluating the different alternative against the quality characteristics of their preferred one. In other words, consumers may have a reference good/supplier on which they differentially evaluate the characteristics of all the other products (Bouckaert, 2000; Madden and Pezzino, 2011). For hospital care, this would mean that some hospital are chosen as reference by the patient and their quality level is used as benchmark in the choice of the preferred provider. Most of the empirical literature assumes that patients are perfectly able to compare hospital quality and that patients choose hospital on the basis of geographical location (proximity) and quality differentiation (Tay, 2003). However, there is some evidence showing that patients perceive hospitals as intrinsically different (Gu and Johar, 2017). Furthermore, to the best of our knowledge, there are no attempts to test whether patients have in mind a reference hospital and select where being treated by comparing the perceived quality of other providers against that supplied by the reference hospital. Thus, the aim of this paper is to investigate whether patients perceptions of hospitals indicators make them elect the best performers in their area as reference providers for a specific treatment. Specifically, we argue that a more reasonable model for competition in this market is to assume that in each local area there might exists an hospital that patients use a reference point on which they evaluate other admission alternatives. Our approach is grounded on a recent theoretical contribution (Levaggi and Levaggi, 2017) which hypothesizes that patients are located around a circle as well as N hospital that compete for patients. The hospitals located on the circle are homogeneous as concerns patients evaluation. However, the hospital that locates at the centre is perceived as being different by consumers and becomes the reference supplier against which all the others compete. In fact the quality and characteristics of the care supplied by the hospital at the centre are used to evaluate all the other alternatives around the circle.

We test such assumption using individual level hospital data covering all admissions for hip-replacement of patients living in Lombardy, Veneto and Emilia Romagna over the period 2013-2016.

2.1.1 Related Literature

Patient choice has been intensively investigated in the empirical literature mostly with reference to the US (Kessler and Geppert, 2005; Tay, 2003; Howard, 2006; Pope, 2009; Wang et al., 2011) ad the UK (Gravelle, Santos, and Siciliani, 2014; Moscelli et al., 2016; Gutacker et al., 2016; Anell, 2015; Moscelli, Gravelle, and Siciliani, 2019); only few studies analyze the same topic in other European countries (Beukers, Kemp, and Varkevisser, 2014; Varkevisser and Geest, 2007a; Varkevisser, Geest, and T.Schut, 2012 for The Netherlands; Moscone, Tosetti, and Vittadini, 2012; Berta et al., 2016 for Italy).

For the US, patients seem to respond to quality signal both in terms of health outcomes such as expected mortality, readmission and complication rates or in terms of quality ranking (Tay, 2003; Howard, 2006; Pope, 2009; Wang et al., 2011) and similar results are reported for the UK (Gaynor, Ho, and Town, 2015; Gaynor, Propper, and Seiler, 2016; Gravelle, Santos, and Siciliani, 2014; Moscelli et al., 2016; Moscelli et al., 2018; Moscelli, Gravelle, and Siciliani, 2019).

Along with the body of literature investigating the relationship between choice, competition and health outcomes a consistent stream of scholarly studies explored the impact of availability of publicly disclosed hospital-level quality measures as drivers of patient preferences. Indeed, a Dutch study (Varkevisser, Geest, and T.Schut, 2012) estimated an average 12% increase of demand as a response to a 1% fall of readmission rates; further, their findings highlight that hospital reputation is a strong driver of hospital choice (65% increase as a response of a 13% increase in reputation point) along with distance. The market for hip replacement has been analyzed with reference to the UK and The Netherlands (Varkevisser and Geest, 2007a; Beckert, Christensen, and Collyer, 2012; Beukers, Kemp, and Varkevisser, 2014; Moscelli et al., 2018; Moscelli et al., 2016). Specifically, Beckert, Christensen, and Collyer (2012) model the demand for elective hip replacements as driven by hospital quality (quality ratings and hospital infections), travel time and hospital production inputs for the purpose of estimating the effect of potential hospital mergers on patient welfare. In their simulation, such policies were observed to reduce hospital competition and therefore relax the incentives to quality improvements, especially in rural areas where the extant competition is lower. Moreover, they highlighted that general practitioners (GPs) have a strong influence on patient choice, indeed patients are more likely to choose hospitals the higher is the number of patients their GP have referred to the same hospital. Such evidence was confirmed by Beukers, Kemp, and Varkevisser (2014) that show that patients prefer to undergo treatment in hospital characterized by higher quality in terms of waiting times and quality ratings with gender-, age- and time-related heterogeneity. Those findings shed light on the fact that measuring hospital quality with readmission rates or mortality rates with case-mix adjustment might induce hospitals to adopt cream skimming in order to improve their published quality indices and attract more patients. Given the flaws of quality indicators based on outcomes (readmission rate, mortality) Gutacker et al. (2016) explained that hospital choice is related to quality measured as the post-surgery variation of self reported health (the PROM questionnaires) as well as distance, waiting time and patient-related unobservable characteristics. Along with reporting that patients dislike to travel for seeking treatment, Gutacker et al. (2016) shown that patient are more responsive to variations in quality as measured in the PROM scores than to traditional outcome-related quality measures. However, the impact of overall hospital quality on patient choice is reported to decrease rapidly as distance increases. All of these models assume that hospitals are differentiated only in geographical location, quality and waiting times and patients are responsive to such differentiation when choosing their preferred hospital. We argue that patients elect a hospital in their local area as a reference point on which they evaluate other admission alternatives. If this is the case, they should have a bias towards these providers, i.e. the probability of patients choosing these hospitals should be higher.

2.1.2 Institutional background

The process of devolution has meant that health care decisions have often been devolved to local Governments tiers which in turn may delegate part of the decision to public and private providers. Devolution is the feature of several European countries such as Austria, Denmark, Germany, Sweden and Spain (Adolph, Greer, and Fonseca, 2012). Compared to other European countries, the process of decentralization of health care in Italy allows for more Regional discretion. In 2001, the devolution of powers from central to regional authorities gave rise to 21 separate health care systems responsible for autonomously funding, organizing and delivering health care services. Regulation enforces that each Italian region have to guarantee the LEA (Livelli Essenziali di Assistenza, essential levels of care) which are a basic bundle of health care services which each citizen is entitled to receive free of charge. However, each region is in charge to implement its own regulation to guarantee the LEA. For hospital care, providers have to compete on quality under a prospective payment system based on Diagnosis Related Groups (DRGs). Each provider receives a fixed DRG tariff based on patients diagnosis (e.g. heart attack) or procedure (e.g. hip replacement) which are set at the beginning of each year. Private hospitals that face a hard budget constraint and must comply with the tariff caps set by the Region. For public hospitals the Region may foresee some form of extra funding and allow them to treat more patients than their set budget would allow them to do.

Within the European context, the Italian framework provides a unique opportunity to explore the effects of competition and decentralization on the quality of health care provided at regional and hospital level in a setting characterized by large jurisdictional differences in hospital capacity, technology endowment, income and financing ability. Indeed, different regional settings may affect hospital competition within and between regions. This might influence patients' perception about hospital quality and, in turn, affect the outcome of competition itself. Indeed, less competitive frameworks may not give hospitals the incentive to maximize their quality.

Among the three analyzed regional health care settings there is a strong degree of heterogeneity in terms of organization and presence of private institutions. Lombardy have adopted a pro-competition regimen in which the regional authority act as a purchaser and controller of health care service trough the presence of territorial entities called *Aziende Sanitaria Locale* (Local Health Authorities, LHA) in charge at a province of lower level. Production of health care is delegated to public and private accredited hospitals. In Lombardy, the presence of private institutions is among the highest among all the Italian regions (29% of total hospital beds versus 23% of the national average). In Veneto the Local Health Authorities have the dual role of purchasers and producers of health care services. This region is characterized by a public competition regimen; indeed, only 9% of the beds are are allocated to private accredited hospitals.

Emilia Romagna have a similar organization to that implemented in Veneto. Indeed, Local Health Authorities own hospitals and are in charge of financing private accredited health care. However, the territorial organization is more centralized: LHAs are defined at aggregation of provinces (*Aree Vaste*, large areas). The presence of private accredited institution accounts for the 17% of hospitals beds. Emilia Romagna was also one of the first Regions to implement a system to manage waiting times (through a Regional Center that sends patients to the hospitals within their neighbor with the lowest waiting time).

2.2 Data

We rely on administrative data on patients who have undergone publicly-funded non-urgent hip replacement from 2013 to 2016 in any public or publicly licensed hospital in the regional health systems of Lombardy, Veneto and Emilia Romagna in Italy (the hospital discharge records, SDO). The dataset comprises a set of socio-demographic characteristics such as gender, age and municipality of residence, principal and secondary diagnosis and type of admission (elective or emergency) . To test whether patients perceptions of true quality indicators make them elect the best performers in their area as reference providers for a specific treatment we integrate the SDO with a panel of publicly available hospital-level hip replacement readmission rates (National Agency for the Regional Health Services, 2019). Readmission rates are the share of patients readmitted to each hospital in the subsequent 30 days from discharge. This indicator is adjusted for concomitant diseases including diabetes, obesity, hematological diseases, cardiovascular disease, neurological diseases and respiratory diseases hence it is readily comparable between hospitals having different case mix.
Given that proximity is highly recognized in the literature as a main driver of hospital demand the obtained dataset was further integrated with the fastest driving distances from the municipality of residence of each patient to the exact position of each hospital. Travel time was calculated by using Stata's user-written packages opencagegeo (Huber and Rust, 2016) and osrmtime (Weber and Péclat, 2017). Patient aged from 14 to 25 where excluded from the sample because for the younger patients hospital choice may be largely based on parents' preferences. Further, we exclude all hip replacements following a hospital transfer. Indeed, hospital transfers are likely based on preferences of the physicians of the hospital from which the patients is being transferred rathern than patient preferences; thus, the freedom of choice might be limited. Hospitals performing less than 50 admissions per year were excluded by the analysis because their obtained readmission rates were not adjusted by National Agency for the Regional Health Services (2019) and hence induce measurement error due to uncontrolled case mix.

2.3 Methods

Our econometric specification is based on the conditional logit random utility model (McFadden, 1974). Specifically, we assume that each patient i faces a choice among J mutually exclusive hospitals from which the individual would acquire an utility U_{ij}, where $j \in J$. Patient i's observed choice occurs only if such utility is maximized on hospital j. Moreover, we assume that utility functions are additive in two components: u_{ij} which depends on patient's and hospital observable characteristics and ϵ_{ij}, a random component encompassing all the unobservable patient and hospital attributes. Hence, $U_{ij} = u_{ij} + \epsilon_{ij}$. If the random components of utility ϵ_{ij} are extreme value distributed and i.i.d. the probability of choosing hospital j for patient i is described by the conditional logit expression (Equation 2.1)

$$P_{ij} = Pr(Y_i = j) = \frac{exp(u_{ij})}{\sum_{k \in J} exp(u_{ik})} \tag{2.1}$$

In order to estimate such model we determine choice sets (i.e. the set of possible hospital chosen by patients) as the set of the 20 closest hospitals to patient i's city of residence, covering a maximum distance of 240 km and a travel time of 3 hours and 15 minutes. Our econometric analysis is concerned to evaluate the deterministic utility functions of patients residing in Lombardy, Veneto and Emilia Romagna, hence separate models are estimated for each region. The deterministic part of the utility for patient i choosing hospital j in year t is represented in Equation 2.2. The subscript t is to be interpreted as the year in which patient i is choosing a hospital for hip replacement. It has to be noted that i and t are jointly determined meaning that we do not observe more than one choice for each patient. However, the subscript t is important because the year in which patient i evaluates the hospitals for undergoing hip replacement is linked with time varying hospital characteristics such as readmission rates and waiting time.

$$u_{ijt} = \alpha_{it} Readmission_{j,t-1} + \beta_{it} Reference_{j,t-1} + \gamma_{it} Wait_{j,t-1} + \delta_{it} Travel_{ij} + \zeta_j \tag{2.2}$$

$Readmission_{j,t-1}$ is the hip replacement readmission rate in hospital j and year $t-1$, quality measure publicly made available by the Ministry of Health through access at the web portal of National Outcome Program (Piano Nazionale Esiti, PNE). The subscript $t-1$ indicates that the variable is lagged by one year to prevent endogeneity. Indeed, a simultaneity bias may be induced by the fact that hospitals with higher levels of demand might have better quality due to economies of learning. To this matter, the literature reports contrasting findings. Judge et al. (2006) evidenced that mortality was higher in higher volume hospitals, Varagunam, Hutchings, and Black (2015) reported no relationship between the two measures. To prevent this possible simultaneity we lag readmission rates by one year, given that actual variation in demand cannot cause variations in past quality levels (Gutacker et al., 2016).
$Reference_{j,t-1}$ is a binary variable which is equal to 1 if hospital j's readmission rate is the minimum in patient i's choice set at the year before the actual choice $t-1$ and zero otherwise. Such variable, when equal to 1, implies that hospital j is the best practice according to quality the metrics disclosed by PNE. As $Reference$ is built upon $Readmission$ the same simultaneity concerns may arise. Thus, we decide to lag it. If this variable is significant and positive, patients are likely to choose the reference in their area more frequently, something that may show that they use this hospital as a benchmark in their choices. $Wait_{j,t-1}$ which is the number of waiting months for hip replacement at hospital j in year $t-1$. As we can only observe waiting time for the observed choice, we calculate $Wait_{j,t-1}$ as the median number of waiting months to each hospital j at time $t-1$ (Sivey, 2012). One year lag is chosen because in our model, endogeneity bias may arise due to the simultaneity of demand and waiting time. Indeed, as pointed out in Riganti, Siciliani, and Fiorio (2017), higher levels of waiting time may lead to a decrease in demand for care. At the same moment, increasing waiting time may be related to higher levels of supply whose behavior we cannot observe. Moreover, simultaneity may lead biased estimates of the waiting time coefficient might arise because hospitals with unobserved attributes of quality correlated with waiting time may attract more patients and, in turn, such increase in demand might lead to higher waiting times due to short run capacity constraints (Gaynor, Propper, and Seiler, 2016; Gutacker et al., 2016). To tackle this issue, we follow the approach of Riganti, Siciliani, and Fiorio (2017) and Gutacker et al. (2016) and lag waiting time by one year as current variations in demand cannot past waiting times.

Further, our model includes as cost variable equal to the fastest driving time in minutes ($Travel_{ij}$) that patient i would need to spend in order to reach hospital j and hospital level fixed effects ζ_j to control for time-invariant unobserved hospital charaateristics.
Concerning patient characteristics, we control for differences in tastes regarding $Readmission$, $Reference$, $Wait$ and $Travel$ by estimating coefficients varying by gender, age and education through the use of interaction terms. Hence, the complete specification of coefficients in Equation

2.2 is the following:

$$\begin{cases} \alpha_{it} = \alpha_0 + \alpha_1 Over75_i + \alpha_2 Female_i + \alpha_3 Educ_i + \alpha_t \\ \beta_{it} = \beta_0 + \beta_1 Over75_i + \beta_2 Female_i + \beta_3 Educ_i + \beta_t \\ \gamma_{it} = \gamma_0 + \gamma_1 Over75_i + \gamma_2 Female_i + \gamma_3 Educ_i + \gamma_t \\ \delta_{it} = \delta_0 + \delta_1 Over75_i + \delta_2 Female_i + \delta_3 Educ_i + \delta_t \end{cases} \tag{2.3}$$

Where $Over75_i = 1$ if patient i is older than 75 years old and zero otherwise, $Female_i = 1$ if patient i is female and zero otherwise and $Educ_i = 1$ if patient have an high school diploma or higher educational achievement and zero otherwise. Parameters to be estimated $\alpha_{it}, \beta_{it}, \gamma_{it}$ and δ_{it}, represent year-specific dummies to capture time variant unobserved heterogeneity in patient's preference with respect to *Readmission*, $Reference$, $Wait$ and $Travel$. A short summary of the variable definition of our model specification is presented in Table 2.1.

Given that the marginal utilities $\alpha_{it}, \beta_{it}, \gamma_{it}$ and δ_{it} convey only information about the sign

Variable	**Description**
$Readmission_{jt}$	Hip replacement readmission rate (%) for hospital j at time t
$Reference_{ijt}$	=1 if hospital j have the lowest readmission rate in patient i's choice set at year t. Equal to zero otherwise
$Wait_{jt}$	Waiting months for hip replacement at hospital j and year t
$Travel_{ij}$	Fastest driving time in minutes from patient i's city of residence to hospital j
$Over75_i$	=1 if patient i is older than 75 years old and zero otherwise
$Female_i$	=1 if patient i is female and zero otherwise
$Educ_i$	=1 if patient have an high school diploma or higher educational achievement and zero otherwise.

Table 2.1: Variable Description

of the impact of the attached variables on patient demand we calculate the elasticities for variables *Readmission*, $Wait$ and $Travel$. Such measures represent the percentage change on the probability of choosing one of the hospitals in the choice set associated to the 1% change in the independent variable of interest. Specifically, for each of the continuous hospital-level variable $(z_{ijt} \neq Reference_{ijt}) \in h_{ijt}$ and attached individual-level coefficient $\mu^z_{it} = \alpha_{it}, \beta_{it}, \gamma_{it}, \delta_{it}$ the estimated elasticity for hip replacement in hospital j for individual i is represented in Equation (2.4). Elasticities are varying over individuals as a consequence of the inclusion of patient-level vector of covariates. The resulting overall elasticity is obtained by averaging η_{ij} over i and j.

$$\eta^z_{ij} = \frac{\partial P_{ij}/P_{ij}}{\partial z_{ij}/z_{ij}} = \frac{\partial P_{ij}}{\partial z_{ij}} \frac{z_{ij}}{P_{ij}} = z_{ij}\mu_{ij}(1 - P_{ij}) \tag{2.4}$$

For the variable $Reference$, the elasticity in Equation (2.4) would not provide any interpretable information given that $Reference$ is defined as binary variable. Hence, we calculate a measure of semielasiticy which represents the percentage change in the probability of choice associated to a unit variation of $Reference_{ijt}$ (i.e. as hospital j would change its readmission rate becoming the best performer in patient i's choice set). Given that β_i is the individual-level coefficient attached to

$Reference$ for patient i the relative measure of semielasticity $\eta_{ij}^{Reference}$ is represented in Equation (2.5). The overall semielasticity of $Reference$ is obtained by averaging η_{ij} over i and j.

$$\eta_{ij}^{Reference} = \frac{\partial P_{ij}/P_{ij}}{\partial Reference_{ij}} = \frac{\partial P_{ij}}{\partial Reference_{ij}} \frac{1}{P_{ij}} = \beta_i(1 - P_{ij}) \tag{2.5}$$

2.4 Results

2.4.1 Descriptive Statistics

Table 2.2 presents the descriptive statistics. The characteristics of the population are quite similar across Regions. About 60% of patients are female and around one third is aged 75 or older. The share of patients with higher education is very similar among the three Regions; however, it is slightly higher in Lombardy. On average, patients travel between 16 and 19 minutes to the chosen hospitals. Patients residing in Lombardy are reported to travel less than their peers from Veneto and Emilia-Romagna. Indeed, even though Lombardy is larger than the other two regions there is much more availability of hospital per squared kilometer. Specifically, Emilia Romagna and Lombardy have similar areas ($22452km^2$ and $23863km^2$) but Lombardy is characterized by almost twice as much hospitals. Furthermore, Lombard patients can choose among 5.28 hospitals in 15 minutes travel time, while patients from Veneto (Emilia Romagna) can choose only between 2(3) hospitals. Even though patients from Veneto travel the most their coefficient of variation is similar to their peers from Lombardy (approx. 83%) while those living in Emilia Romagna travel on average 17 minutes but are characterized by a greater variability (coef. of variation approx. 97%).

	Lombardy		**Veneto**		**Emilia Romagna**	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Travel Time	16.532	13.834	19.048	15.977	17.221	16.756
Waiting Time (months)	3.915	2.174	5.321	2.805	5.727	3.227
Female	0.617	0.486	0.601	0.490	0.625	0.484
Over75	0.343	0.475	0.344	0.475	0.329	0.470
High Education	0.184	0.388	0.157	0.364	0.157	0.364
Number of admissions	41166		26062		16426	
Number of hospitals (range)	86-88		39-44		48-53	

Table 2.2: Descriptive Statistics

Concerning hospital quality attributes, readmission rates of the average hospital (blue lines if Figure 2.1) are steady through the years in Lombardy, while in Veneto and Emilia Romagna the time-variation of readmission is higher. Further, the variability of readmission rates in Emilia Romagna and Lombardy is constant through the years. The former region have less variability than the latter. In Veneto, standard deviation of readmission rate is less stable being the maximum in 2015 and the minimum in 2016 if compared with all regions and years. Waiting time is lower in Lombardy and also less variable, while Emilia Romagna and Veneto have similar figures in both mean and standard deviation of waiting time. Interestingly, Emilia Romagna have the least variability of readmission rates and the highest variability of waiting time. In general, reference hospitals have zero readmission rates (green line in Figure 2.1), indicating that patients have at least one alternative with very high quality in their alternative sets (the 20 closest hospitals). Although patients are reported to always have a best performer in term of readmission rates the share of patients choosing their best option is extremely varying in two of the three regions. Indeed, in Lombardy such share increases from 0.7% in 2015 from 13% in 2016 because in the latter year, there were many private hospitals that achieved zero readmission rates. In Emilia-Romagna this phenomenon is occurring in the second year. On the contrary, in Veneto the share of patients choosing reference hospitals is more stable.

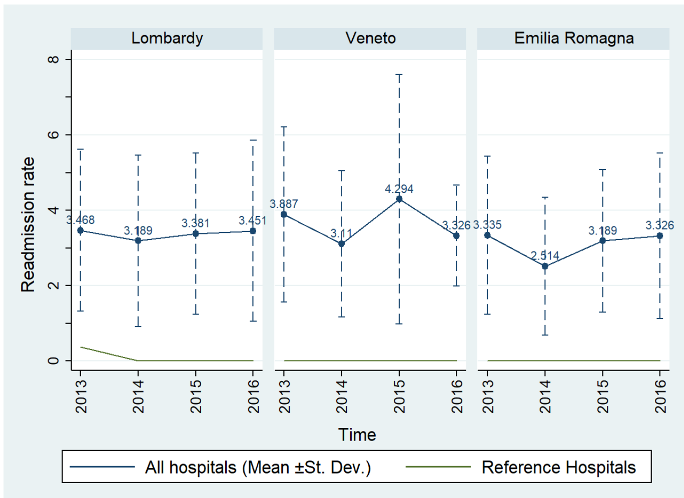


Figure 2.1: Readmission rates by year and region

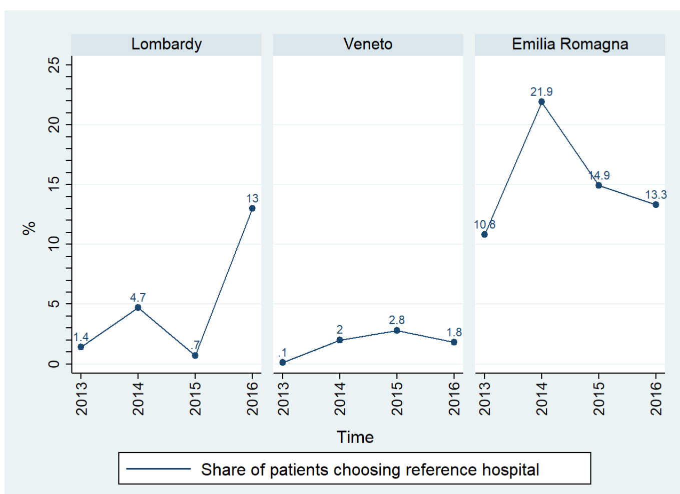


Figure 2.2: Share of patients choosing reference hospitals

2.4.2 Regression Results

Table 2.3 summarizes the estimation results for equation 2.2. The evaluation that patient do for reference hospitals is heterogeneous in terms of Region, level of education and gender. On average, only patients residing in Veneto give a positive marginal utility to hospitals having the minimum possible readmission rate regardless their age. However, the more educated patients living in the same region seem to evaluate negatively the reference hospitals. This behavior may have several explanations: less educated patients may rely more on GP's advice and the latter may make a choice more biased towards hospitals with better quality indicators. On the other hand, readmission does not seem to be an important element on which to choose, apart from females.

In Lombardy, the region where competition among hospitals should be more intense (large presence of private hospitals and long tradition for a mixed market) only the female seem to be significantly willing to undergo treatment in reference hospitals. Furthermore, patients residing in Emilia Romagna do not significantly increase their utility by choosing a reference hospital, this is consistent across age groups, education and genders. The variability of quality indicators is the least, hospitals may be perceived as having the same level of quality. On average, reference elasticities are positive in Veneto and Emilia Romagna, with the former patients being more responsive than the latter (elasticity equal to 0.14 in Veneto and 0.08 in Emilia Romagna). Concerning the quality indicators released annually by the Ministry of Health (the readmission rates) our results show that quality indicators might be misperceived: patients seeking for treatment in Lombardy and Emilia Romagna are more likely to choose hospitals with higher readmission rates with the exceptions of females from Emilia Romagna. Such finding related to gender is also consistent in Veneto. This may mean that patients misperceive quality, or that they choose their hospital using other information such as reputation that do not reflect the true quality levels. Travel time and waiting time are the most important variables on which patients make their decision. In all regions patients are on average unwilling to travel farther, with patient-level heterogeneity according to education and age groups. Our travel time elasticity estimates are above all those reported in previous empirical contributions (Varkevisser, Geest, and Schut, 2010), regardless of the regional health care system in which they are enrolled to; interestingly, our elasticity estimates are approximately ten to forty times waiting time elasticity, suggesting that patients are mostly considering proximity when choosing their preferred hospital. Moreover, patients seeking for care in Lombardy and Emilia Romagna are as responsive to waiting time as reported by the current body of literature (Riganti, Siciliani, and Fiorio, 2017; Varkevisser, Geest, and T.Schut, 2012); while demand of patients from Veneto is far more elastic (elasticity equal to -0.431). Significant education-related heterogeneity for preferences in terms of waiting time is common to all of three regions while only the residents of Veneto and Emilia-Romagna are characterized by heterogeneous preferences in terms of gender. In general, patients from Lombardy base their choice mainly of travel time and waiting time, while there seems to be misperception of publicly available quality measures. Interestingly, patients in Veneto seem to use the hospital that has the lowest readmission as a reference supplier, however they do not consider readmission rates *per se*. On the other hand, they are also less willing to wait. This may reflect the fact that in a public competition as the one that characterize the Veneto Region, the quality of hospitals is perceived to be more or less the same, perhaps also because hospitals are not aggressive competitors. For this reason, waiting time becomes very important. In Emilia Romagna, where both competition and variability of quality indicators are limited, the choice of hospitals seems to be mainly driven by proximity and, commonly with Lombardy, readmission rates seems to be misperceived.

Table 2.3: Results

	Lombardy	Veneto	Emilia-Romagna
Reference	-0.036	0.304*	0.107
	(0.073)	(0.125)	(0.104)
Readmission	0.029***	0.014	0.031*
	(0.008)	(0.013)	(0.015)
Travel	-0.118***	-0.095***	-0.087***
	(0.001)	(0.001)	(0.001)
Wait	-0.027***	-0.029***	-0.02
	(0.008)	(0.009)	(0.012)
Interactions with Reference			
- Educ	-0.086	-0.741*	0.247
	(0.183)	(0.370)	(0.262)
- Female	0.132*	-0.079	0.04
	(0.065)	(0.093)	(0.088)
- Over75	0.045	0.266**	0.052
	(0.066)	(0.095)	(0.090)
Interactions with Readmission			
- Educ	0.025	0.007	0.001
	(0.013)	(0.023)	(0.032)
- Female	-0.006	-0.029***	-0.029*
	(0.006)	(0.008)	(0.011)
- Over75	-0.003	0.020*	-0.014
	(0.006)	(0.008)	(0.012)
Interactions with Travel			
- Educ	0.051***	0.022***	0.016***
	(0.003)	(0.003)	(0.003)
- Female	-0.002	0.001	0.002
	(0.001)	(0.001)	(0.001)
- Over75	-0.017***	-0.013***	-0.019***
	(0.001)	(0.001)	(0.002)
Interactions with Wait			
- Educ	0.112***	0.039*	0.127***
	(0.011)	(0.016)	(0.015)
- Female	-0.009	-0.018**	-0.017**
	(0.006)	(0.006)	(0.006)
- Over75	-0.004	-0.005	-0.007
	(0.006)	(0.006)	(0.006)
Reference Semielasticity	-0.120	0.143	0.084
Readmission Elasticity	0.0398	0.0169	0.003
Wait Elasticity	-0.0926	-0.431	-0.144
Travel Elasticity	-3.465	-3.744	-3.132
Hospital Fixed Effects	Yes	Yes	Yes
Interaction with time			
Reference	Yes	Yes	Yes
Readmission	Yes	Yes	Yes
Wait	Yes	Yes	Yes
Travel	Yes	Yes	Yes

Standard errors in parentheses, *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 2.4: Robustness check of readmission rates

	Lombardy	Veneto	Emilia-Romagna
Reference	-0.096	0.267*	-0.046
	(0.071)	(0.118)	(0.091)
Travel	-0.118***	-0.095***	-0.086***
	(0.001)	(0.001)	(0.001)
Wait	-0.026**	-0.028**	-0.014
	(0.008)	(0.009)	(0.011)
Interactions with Reference			
-Educ	-0.157	-0.763*	0.256
	(0.178)	(0.360)	(0.242)
-Female	0.150*	0.025	0.130
	(0.063)	(0.088)	(0.080)
-Over75	0.053	0.195*	0.098
	(0.064)	(0.091)	(0.082)
Interactions with Travel			
-Educ	0.051***	0.021***	0.016***
	(0.003)	(0.003)	(0.003)
-Female	-0.002	0.001	0.002
	(0.001)	(0.001)	(0.001)
-Over75	-0.016***	-0.013***	-0.019***
	(0.001)	(0.001)	(0.002)
Interactions with Wait			
-Educ	0.113***	0.039*	0.126***
	(0.012)	(0.016)	(0.015)
-Female	-0.01	-0.015*	-0.018**
	(0.006)	(0.006)	(0.006)
-Over75	-0.004	-0.007	-0.008
	(0.006)	(0.006)	(0.006)
Reference Semielasticity	-0.150	0.151	0.0541
Wait Elasticity	-0.0884	-0.418	-0.123
Travel Elasticity	-3.464	-3.731	-3.127
Hospital Fixed Effects	Yes	Yes	Yes
Interaction with time			
Reference	Yes	Yes	Yes
Wait	Yes	Yes	Yes
Travel	Yes	Yes	Yes

Standard errors in parentheses,*** p<0.001, ** p<0.01, * p<0.05

Robustness analysis

We assess the robustness of the previous results by considering two additionals models: i. a model excluding readmission rates and its interactions from Equation 2.2; ii. a model consistent with Equation 2.2 including the dummy variable $Over65$ instead of the variable $Over75$; iii. a pooled model, which allows patients to choose hospitals outside their regional borders. The first robustness check tests whether the results obtained about the $Reference$ variable holds when quality indicators disclosed by PNE are not considered in the choice process. The second tests whether the categorical specification of age may affect the results. The last model is aimed to test whether restriction of choice sets to regional borders may affect estimated results. This model allows patients living in provinces nearby the region borders to choose hospitals in other regions. When considering the first robustness (Table 2.4) check it can be noticed that the variable $Reference$ maintains its significance across regions confirming that, while in Lombardy and Emilia-Romagna patients do not tend to seek for care in their best options according to the readmission rates, patients from Veneto tend to base their choice on whether a hospital is the best-practice among their possible alternatives. Heterogeneity due to personal characteristics is consistent with findings reported in Table 2.3. Results obtained for $Travel$ and $Wait$ are also consistent with previous findings. The robustness check specifying age as $Over65$ (Table 2.5) does not show variation in terms of significance or magnitude of coefficients. Particularly, patients from Veneto are more likely to choose a hospital if is the reference among their possible alternatives. In Lombardy and Emilia-Romagna patients the relationship between choice and reference hospitals is not significant. Heterogeneity due to personal characteristics is consistent with findings reported in Table 2.3. The estimated coefficients for $Readmission$, $Travel$ and $Wait$ are also robust to the specification of age. Further, consistent findings are estimated for personal characteristic-related heterogeneity of preferences in terms of education and gender.

The pooled model (Table 2.6) evidences that, when patients are allowed to choose hospitals outside their region, there is no overall evidence of patients being more willing to choose the hypothesized reference hospital (i.e. the best hospital in terms of quality indicators from the Ministry of Health). This effect is consistent regardless the age groups, gender and education levels. This specification gives further evidence on patients being more willing to choose hospitals with higher readmission rates. Specifically, such evidence is less strong in terms of magnitude for females. Even though this effect is significant, average elasticities highlight that the impact of readmission rates is negligible when confronted with the impact of proximity. Specifically, a percent increase in readmission rates leads to an increase of probability of choice of 0.065 %, while the same relative increase in terms of travel time leads to a decrease of probability of choice equal to 3.34%. The pooled specification confirms also that waiting time is taken into account at the moment of hospital choice. Again, its effect is negative and much lower than what observed for travel time. Patient-level heterogeneity is present in terms of genders and education.

Table 2.5: Robustness check of age

	Lombardy	Veneto	Emilia-Romagna
Reference	0.001	0.293*	0.067
	(0.088)	(0.140)	(0.117)
Readmission	0.031***	0.016	0.031*
	(0.008)	(0.013)	(0.015)
Travel	-0.118***	-0.095***	-0.087***
	(0.001)	(0.001)	(0.001)
Wait	-0.027***	-0.029***	-0.020
	(0.008)	(0.009)	(0.012)
Interactions with Reference			
-Educ	-0.310	-0.936*	0.235
	(0.190)	(0.410)	(0.264)
-Female	0.111	-0.145	0.098
	(0.065)	(0.092)	(0.088)
-Over65	0.002	0.187	0.041
	(0.073)	(0.102)	(0.087)
Interactions with Readmission			
-Educ	0.021	0.005	-0.000
	(0.014)	(0.023)	(0.032)
-Female	-0.007	-0.031***	-0.026*
	(0.006)	(0.008)	(0.011)
-Over65	-0.004	0.015*	-0.016
	(0.006)	(0.008)	(0.011)
Interactions with Travel			
-Educ	0.051***	0.021***	0.016***
	(0.003)	(0.003)	(0.003)
-Female	-0.002	0.001	0.002
	(0.001)	(0.001)	(0.001)
-Over65	-0.017***	-0.013***	-0.019***
	(0.001)	(0.001)	(0.002)
Interactions with Wait			
-Educ	0.112***	0.039*	0.126***
	(0.012)	(0.016)	(0.015)
-Female	-0.009	-0.018**	-0.016**
	(0.006)	(0.006)	(0.006)
-Over65	-0.003	-0.005	-0.008
	(0.006)	(0.006)	(0.006)
Reference Semielasticity	-0.089	0.204	0.054
Readmission Elasticity	0.043	0.012	0.005
Wait Elasticity	-0.093	-0.430	-0.144
Travel Elasticity	-3.466	-3.744	-3.132
Hospital Fixed Effects	Yes	Yes	Yes
Interaction with time			
Reference	Yes	Yes	Yes
Wait	Yes	Yes	Yes
Travel	Yes	Yes	Yes

Standard errors in parentheses,*** p<0.001, ** p<0.01, * p<0.05

Table 2.6: Pooled model

	Pooled Model
Reference	0.076
	(0.086)
Readmission	0.024**
	(0.008)
Travel	-0.114***
	(0.001)
Wait	-0.081***
	(0.009)
Interactions with Reference	
-Educ	0.027
	(0.074)
-Female	-0.043
	(0.060)
-Over75	-0.010
	(0.063)
Interactions with Readmission	
-Educ	-0.002
	(0.007)
-Female	-0.023***
	(0.005)
-Over75	-0.003
	(0.006)
Interactions with Travel	
-Educ	0.032***
	(0.001)
-Female	-0.001
	(0.001)
-Over75	-0.012***
	(0.001)
Interactions with Wait	
-Over75	0.006
	(0.005)
-Female	-0.021***
	(0.005)
-Educ	0.123***
	(0.006)
Reference Semielasticity	0.0539
Readmission Elasticity	0.0648
Wait Elasticity	-0.127
Travel Elasticity	-3.341
Hospital Fixed Effects	Yes
Interaction with time	
Reference	Yes
Wait	Yes
Travel	Yes

Standard errors in parentheses, *** $p<0.001$, ** $p<0.01$, * $p<0.05$

2.5 Discussion and conclusions

In this work we test for the presence of reference providers using data for hospital admission for hip replacement for Lombardy , Veneto and Emilia Romagna for the period from 2013 to 2016. These regions are heterogeneous in terms of presence of private providers and geographical spread of hospitals. The novel feature of our model is the inclusion of the hospital that has the best performances in terms of quality. We use readmission rate as an objective measure of the latter and for each patient we have determined which would be its best choice by comparing the readmission rates of the 20 closest hospitals to each patient, covering a maximum travel time of approximately 3h15' and a radius of 241 km. With this information we have defined the variable that will be used to test for the hypothesis that patients compare quality of the alternatives in their area with a reference hospital (the one with the best verifiable level).

Our work highlighted that patients seems to elect reference hospitals only in Veneto, where the competition is mostly among public hospitals given that presence of private providers is the most limited. In such region, the variance of readmission rates varies strongly over the years; thus patients (or their GPs) might be more informed about hospital quality levels. Given such heterogeneity in variability patients may be more informed about hospital quality and choose their best option. Furthermore, patients seem to trade off reference hospitals with proximity and waiting time while we observe no significant effect of readmission rates per se. This would mean that, all other factors being equal, non-reference hospitals are perceived as the same by patients. Even though we did not find any evidence of reference hospitals in Lombardy and Emilia Romagna. The counter-intuitive significant positive coefficient of readmission rates poses questions for future research. Indeed, it seems that patients from Lombardy and Emilia-Romagna (the regions with higher share of private hospitals) tend to choose hospitals with lower level of quality, all other factors being equal. Readmission elasticity is very low for patients in these two regions: a 1% increase of readmission rate implies an increase in demand of 0.005% in Emilia Romagna and 0.04% in Lombardy suggesting that this effect is negligible with respect to variations in travel time. These results might be explained by incomplete information, corroborating the results obtained in Berta et al. (2016): even though information about hospital quality is available patients (or their referring physician) do not rely on it. The policy implications in this findings would be related to the ability of making quality information available to patients, for instance by simplifying the access to it.

This work does not come with limitations that may represent avenues for future research. First, hospital choice is related also to the preferences of referring physicians for which data were not available: physicians might advice patients to undergo treatment institutions for other reasons that are negatively correlated with quality. Therefore, it would be worth investigating GP behavior in order to provide greater understanding of hospital choice. Second, our model only takes into account intra-regional mobility without allowing patients to choose hospital outside their regional framework. However, in the Italian context extra-regional mobility is a remarkable phenomenon. Thus, it would be interesting to study whether patients elect reference hospitals when all the regional health care systems are able to compete. Specifically, the least restrictive in terms of mobility was allowing patient interchange among the three regions. However, border effects exist to regions other than Lombardy, Emilia Romagna and Veneto.

Chapter 3

Outpatient choice: evidence from a Lombardy Local Health Authority

This chapter is derived from the working paper "Outpatient provider choice in the Italian healthcare system." in coauthorship with Mattia Cattaneo, Paolo Malighetti, Gianmaria Martini and Alberto Zucchi. It was firstly presented at DREAMT/AEM workshop on 08/02/2019. I am responsible for all the changes in this chapter

Abstract

There is a consistent body of literature studying the nature of patient choice in health care systems where prices are fixed due to regulation with a large focus on inpatient choices for elective treatment in a hospital framework. However, outpatient provider choice have been little investigated. The aims of this study are to investigate the healthcare provider choices of outpatients undergoing public cardiological first examinations in Northern Italy where hospitals and outpatient-only providers compete and to apply our econometric model to simulate variations in provider characteristics. Mixed logit model was used to analyze outpatient provider choice from a rich and overlooked administrative dataset, publicly available provider-level data and travel time were calculated using Google Maps. Outpatients are more responsive to changes in waiting times and less responsive to travel times than inpatients. They are more likely to seek for consultations from providers located in their district of residence and those signaling more experience in highly specialized related disciplines. Our policy simulation and elasticity estimates highlight the extent to which the closure of a local provider can impact the redistribution of outpatients showing that patients base largely their choice on proximity and can provide policymakers guidance concerning the territorial planning of outpatient care in case of provider closure.

3.1 Introduction

Currently, health care systems are pushing towards the reduction of health care costs by focusing on prevention. In this framework, outpatient care procedures such as specialist consultations and instrumental tests are crucial for public health systems, as they can mitigate and prevent declines in patient health, and thus reduce inpatient care costs (Santos, Gravelle, and Propper, 2017). Indeed, many policies finalized at prevention and early disease detection are based on outpatient procedures. Remarkable examples of such policies are the screening programs implemented in Italy for breast and colorectal cancer which are based on tests performed without hospitalization. Further, physician consultations may inform patients about risk factors such as unhealthy dietary regimens, lead to correct such behaviors and eventually prevent future hospitalizations and costs for more complicated pathological conditions.

The outpatient sector accounts for a significant portion of government health care expenditures; indeed OECD countries on average spend 28 % of their health care budget on outpatient services. Concerning European countries having universal coverage and freedom of provider choice the fraction of outpatient expenditure on the total is 32 % for Italy, 29% for the UK and 26 % for the Netherlands (OECD, 2017).

Nonetheless, the current body of research largely focused on investigating the mechanisms underlying inpatients' provider choice by analyzing elective procedures such as delivery (Phibbs et al., 1993), hip replacement (Beukers, Kemp, and Varkevisser, 2014), coronary artery bypass graft (Wang et al., 2011), and cataract surgery(Sivey, 2012). Given the aforementioned gap in the literature the aim of this study is to analyze the mechanisms underlying patient choice for outpatient first examinations (i.e., a doctor's initial examination of an outpatient within a specific clinical branch).

Even though outpatients are likely to base their choice on a set of similar determinants, such as hospital proximity quality and waiting time, these factors may play different roles in the outpatient setting. Proximity have been widely recognized as the main driver of patient choice in the inpatient framework. Indeed, there is wide consensus that patients having free hospital choice prefer closer hospitals (Varkevisser, Geest, and Schut, 2010). In the outpatient framework competition is characterized by hospitals but also by providers which specialize in outpatient services without delivering any inpatient procedure. Thus, outpatients have larger alternatives sets and may be more willing to substitute a provider with another than inpatients (i.e. more sensitive to variations in travel time).

Concerning quality, the current body of research recognizes that inpatients are responsive to publicly available information concerning hospitals. Specifically it have been reported that patients are more likely to choose hospitals with lower mortality (Beckert, Christensen, and Collyer, 2012). However, Gutacker et al. (2016) recognized that condition-specific quality measured based on outcomes (i.e. mortality, readmission) convey little information about the health improvements, which are the final goals of treatments. The same scholars acknowledged that patients are willing to choose hospitals giving higher self-reported health gains to previous patients. Concerning outpatients, the literature gives limited evidence in terms of quality of outpatient examinations. Outpatient examination quality indicators are not available as there are no adverse outcomes (i.e. death, readmission) or short term health improvements related to outpatient procedures (physician visits, instrumental tests). To our knowledge, the only evidence mentioning outpatient quality is Varkevisser and Geest (2007b). In their framework, outpatient consultations are carried out in hospitals and their quality proxies are based on type of hospital (teaching versus non-teaching) and hospital size. They report that patients are likely to undergo orthopedic and neurosurgery visits in teaching hospitals smaller hospitals to the point of bypassing the nearest hospital. Although Italian inpatients can retrieve quality information on hospital procedures as disclosed by the Ministry of Health through the web portal of National Outcome Program (Piano Nazionale Esiti), metrics concerning outpatient care quality are undisclosed and unknown by outpatients; this lack of information may lead patients to rely strongly on feedback gathered from their peers (Berta et al., 2016; Moscone, Tosetti, and

Vittadini, 2012) , their general practitioner (GP) or on their perception about provider's medical knowledge.

Lastly, waiting time have been recognized a determinant of inpatient choice. Indeed, two Dutch studies (Varkevisser and Geest, 2007a; Varkevisser, Geest, and T.Schut, 2012) acknowledged that inpatients and outpatients are less likely to choose hospitals with higher waiting times to the point of bypassing the nearest hospital.

Another unique feature of outpatient care is that examinations occur earlier during the patient–provider interaction than inpatient procedures. Hence, patients' choices are less constrained by previous decisions. Indeed, while inpatients generally go through a sequential decision-making process involving multiple physicians, providers, and caregivers, outpatients are just beginning their interaction with health care providers with respect to their specific suspect health problems. This fact may also affect their psychological perception of waiting for care: patients waiting for a first specialist consultation suffer from higher uncertainty about their physical condition, which might influence their willingness to wait.

In light of the differences between the inpatient and outpatient setting, we aim to contribute to the literature in two fashions: first, by empirically analyzing the determinants of provider choice for outpatient examinations and second by proposing our empirical model as a decision making tool for drawing policy implications for decision makers who want to organize outpatient services with the goal of improving public providers' economies of scale and learning. Thus, we use our estimates to simulate the closure of a provider.

For this purpose, we use prescription level data obtained from the Local Health Authority (LHA) of the Province of Bergamo which belongs to the regional health care system of Lombardy, Italy. Data include information on prescriptions, patients, and health care providers concerning the use of outpatient services for 15,913 cardiological first examinations ("prima visita cardiologica"; International Classification of Diseases procedure code 89.7A.2) in 2015.

3.2 Institutional Setting

In Italy, universal health coverage is financed through general taxation; organization and provision of health care is delegated to regional goverments. Among the Italian regions, Lombardy adopted a competition-based healthcare model in which patients are free to choose their preferred institution within the regional territory. In such region, public and private institutions are allowed to deliver health care on behalf of the regional health care system. In Lombardy, health care institutions providing public health services are reimbursed through prospective payments schemes; acute hospital care is financed by Diagnosis Related Groups, while outpatient care is funded by a system called "nomenclatore tariffario" (funding classifier) which sets the reimbursement each provider would receive. Patients are allowed to access public health care services after having obtained a prescription from their GP located in their municipality of residence or a specialist; once the prescription is obtained, they can choose any of the providers authorized by regional health service of enrolment regardless of their ownership. Prior to access public health services patients are charged a copayment ("ticket"). The regulation provides that the most fragile parts (severely ill, disabled, elderly and low income) of the population are exempted for such copayment. Specifically, income exemption is given to the unemployed, to families whose yearly income is below approximately 8000 Euro, to older adults earning approximately 36000 Euro per year and social pensions recipients. Moreover, patients suffering from a set chronic diseases are eligible to the exemption, given that the prescription is related to their pathology (Berta et al., 2017). At the local level, health care purchase is managed by province-level local health authorities (LHA), which in turn delegate management, integration and coordination of outpatient care to lower-level municipality-based entities called districts. Their main aim is to ensure universal access, integration and coordination between outpatient care providers and GPs within their territory.

3.3 Data

We evaluate the determinants of patient choice in the ambulatory setting using data on cardiological first examinations undertaken at the LHA of the Province of Bergamo, northern Italy. The data cover 15,913 visits from January 1, 2015 to December 31, 2015. For each cardiological visit, the data report the waiting time and the characteristics of each provider (35 in total)—including the provider's geographical location, whether it is a hospital or provides only ambulatory services, and its legal status (public or private)—as well as information about outpatient activities, such as diagnostic exams and specialist visits. Each provider is identified inside a coordinating district within the province and could be part of a hospital trust; moreover, providers may be hospitals or institutions which deliver only outpatient procedures. We also consider the patient's age, gender, and municipality of residence. We investigate how the spatial structure of the outpatient setting might affect patient choice by associating the fastest driving time option with each origin-destination pair (from the patient's home to the provider's address). Our sample is focused on non-urgent elective visits and thus excludes all those complicated patient whose choice is based on serious emergent health care issues.

3.4 Methods

3.4.1 Estimation

We base our empirical analysis on random utility theory (McFadden, 1973). In this framework the outpatient's utility U_{ij} in choosing cardiological visit provider j from alternative set J is formed by two addictive components. The first component, u_{ij}, depends from a vector of observed provider characteristics $\boldsymbol{x_j}$; the second, ϵ_{ij}, is random and encompasses unobserved (to the researcher) provider attributes. Parameter vector $\boldsymbol{\beta}$ is to be estimated and represents tastes of patient i over provider attributes $\boldsymbol{x_j}$ (Equation 3.1).

$$U_{ij} = u_{ij} + \epsilon_{ij} = \boldsymbol{\beta x_j} + \epsilon_{ij} \tag{3.1}$$

Each patient is assumed to undergo a visit to a provider such that her utility U_{ij} is maximized. We assume that the alternative set J is composed of each public (or publicly licensed) provider located in the Province of Bergamo. This assumption is motivated by the fact that, in our framework, patients have already expressed their willingness to forego private consultations by obtaining a regional health care system prescription from their GP. Under the assumption that ϵ_{ij} is independently and identically distributed (i.i.d.) as a type 1 extreme value function, the conditional probability p_{ij} that outpatient i chooses provider j is given by the conditional logit function (Equation 3.2).

$$p_{ij} = \frac{exp(u_{ij})}{\sum_{k \in J} exp(u_{ik})} \tag{3.2}$$

We relax the assumption of proportional substitution between alternatives (independence of irrelevant alternatives, IIA) that characterizes the standard conditional logit model (Equation 3.2). For this purpose, we fit a mixed logit model, which allows to measure unobserved heterogeneity in patients' preferences (Train, 2009). Such modeling approach allows taste parameters $\boldsymbol{\beta}$ to vary randomly across outpatients with density distribution $f(\boldsymbol{\beta})$, which is a priori specified while its parameters are to be estimated. The unconditional choice probability P_{ij} for individual i to choose provider j is given by the integral of the conditional logit probability over the density distribution of $\boldsymbol{\beta}$ (Equation 3.3).

$$P_{ij} = \int p_{ij} f(\boldsymbol{\beta}) d\boldsymbol{\beta} = \int \frac{exp(u_{ij})}{\sum_{k \in J} exp(u_{ik})} f(\boldsymbol{\beta}) d\boldsymbol{\beta} \tag{3.3}$$

The integral in Equation 3.3 does not have a closed form, it is approximated through simulation (Train, 2009). Given that coefficients $\boldsymbol{\beta}$ do not convey information about the magnitude of variation in probability of choice given a change in a covariate we calculate the elasticities of waiting and travel times following Sivey (2012). Given a provider-specific continuous variable x_j The procedure is the following:

1. Obtain $P^0_{ij} = P_{ij}(x_j)$, the probability of choosing outpatient provider j for individual i conditional on the value of x
2. For each provider j calculate $x^{'}_j = 1.01 * x_j$, the 1 % increase of variable x_j
3. For each provider j evaluate the probability $P^1_{ij} = P_{ij}(x^{'}_j)$
4. Calculate the individual level elasticity of choosing provider j as $\eta^x_{ij} = \frac{P^1_{ij} - P^0_{ij}}{P^0_{ij}}$
5. calculate η_x, the average of η_{ij} over i and j as reported in Equation 3.4

$$\frac{1}{N} \sum_{j \in J} \sum_{i=1..N} \frac{P_{ij}(x^{'}_j) - P_{ij}(x_j)}{P_{ij}(x_j)} \tag{3.4}$$

3.4.2 Model Specification

We formulate our choice model by assuming that the deterministic part of the utility function u_{ij} (Equation 3.1) depends on the driving time from patient i's city of residence centroid to the provider j of destination ($Travel_{ij}$) which was obtained from Google Maps. Our model specification includes also waiting time. However, we only can observe individual waiting time $Wait_{ikt}$, the time that patient i had waited to undergo a visit to provider k at month t. This leads that we do not observe the time patient i would have waited if she chose a provider j different than k at the same month t. In order to overcome such limitation, we use the same procedure as Sivey (2012). Specifically, we include $Wait_{jt}$ which is the provider-specific waiting time: such metric is calculated from actual waiting times by obtaining the median waiting time at provider j in month t. The median is preferred to mean because it is robust to the presence of outliers. However, given that quality is unobservable, patients may interpret longer waiting times as an indirect quality signal and therefore be attracted to providers with longer waiting lists; meanwhile, providers becoming more attractive among outpatient care providers might increase their waiting times due to capacity limits. Thus, outpatient choice and waiting time may be simultaneously determined (Gaynor, Propper, and

Seiler, 2016) and leading to endogeneity issues that may produce biased estimates of the impact of waiting time on patient demand for outpatient services. Thus, we follow the approaches outlined in Gutacker et al. (2016) and Riganti, Siciliani, and Fiorio (2017) by using 3-months lagged waiting time as instrument. The resulting F-statistic for relevance of the instrument is equal to 10.18 and greater than 10, suggesting strong relevance (Angrist and Pischke, 2014). Hence, $Wait_{jt}$ is replaced by $Wait_{jt-3}$ Our model also includes a vector of provider characteristics, composed by the total number of inpatient services ($Volume_{jt}$), the legal status ($Private_j$), and the fact that provider j is a hospital and delivers inpatient care ($Hospital_j$).

Still, provider volume and demand for outpatient visits could be simultaneously determined, given that health care providers with higher volumes might be perceived as higher-quality by patients and therefore more attractive (Gutacker et al., 2016). We tackle such possible endogeneity by including a different variable: the annual volume of non-cardiovascular outpatient services (F-statistic for relevance equal to 40.32, (Angrist and Pischke, 2014). We assume that this measure is correlated with the volume of cardiological services but not with the unobserved quality attributes of cardiological inpatient examinations. However, the chosen instrument of volume might be correlated with unobserved overall provider quality and thus bias the estimates. In such case, the instrument would be invalid and would introduce a bias in coefficient estimate of $Volume_{jt}$ which direction depends on the sign of the true coefficient of the unobserved quality and on the sign of the correlation between volume and the unobserved overall quality. In this regard, hypothesizing that patients are sensible to provider quality would imply that the former is positive. Thus, our coefficient estimate for $Volume_{jt}$ would be downward biased if volume and quality are positively correlated and would be upward biased otherwise.

Moreover, our model accounts for the fact that the provider allows patients the opportunity to undertake cardio-surgical specialist visits ($OutSurg_j$) or may perform cardio-surgical procedures ($InSurg_j$). These variables are of particular interest because they reflect the provider's capacity of treating more complex cardiological cases. Specifically, $OutSurg$ and $InSurge$ may provide indirect quality information to patients facing an outpatient visit, which may end up in being more complicated and face surgery. At the territorial level, we test whether GPs tend to refer patients to providers located in their district ($District_{ij}$). Since organizational units coordinate outpatient care activities, clinicians working in the same district are more likely to know each other through participation in coordinating activities within the district.

In our model we also want to take into account possible heterogeneity in preferences related to observed and unobserved patient characteristics. Thus, we control for observable preference heterogeneity between patients by including in our specification interaction terms between $Travel$ and $Wait$ with patient demographic characteristics ($Over65$ and $Female$). Moreover, preference heterogeneity related to $Travel$ and $Wait$ is controlled for also in terms of income or health status. To this matter, we include the binary variables $ExemptFrail_i$ and $ExemptIncome_i$: the former is equal to 1 when a patient is exonerated from the 36 Euro ticket due to presence of comorbidities and 0 otherwise, the latter is equal to 1 when a patient is exempted from the copayment because of unemployment or low income. Being patient-level variables, $ExemptFrail_i$ and $ExemptIncome_i$ are interacted with $Travel$ and $Wait$. Further, we allow preferences in terms of Travel time and Waiting time to be heterogeneous across individuals due to unobservables by including log-normally distributed random components for $Travel$. Log-normality is preferred to normality or to other distributions defined in the real space because it implies that every patient have a coefficient constrained in sign (i.e. being negative or positive). In our framework, we expect the Travel Time coefficient to be negative for all patient, since traveling to further providers is related to a welfare loss on individuals (Lippi Bruni, Ugolini, and Verzulli, 2018). We free this assumption for Waiting Time, given that we cannot assume any coefficient sign for all of the patients because waiting time might be interpreted an indirect quality signal; therefore, we assume normally distributed random components for Waiting time. A brief summary of the covariates is reported in Table 3.1.

Table 3.1: Variable Description

Variable	**Description**
$Travel_{ij}$	Travel time in minutes from patient i's household to provider j.
$Wait_{jt-3}$	Three months lagged median waiting days for the first cardiological visit at provider j
$Hospital_j$	=1 if the provider is a hospital, 0 otherwise. Interacted with $Travel$ and $Wait$
$InSurge_j$	=1 if the provider carries out cardio-surgical outpatient visits, equal to 0 otherwise.
$OutSurge_j$	=1 if the provider performs cardio-surgical interventions, equal to 0 otherwise.
$Volume_{jt}$	Annual number of non-cardiological inpatient services of provider j
$Private_j$	=1 if the provider is privately owned, 0 otherwise.
$District_{ij}$	=1 if the patient and the selected provider are located within the same LHA district, 0 otherwise.
$Gender_i$	=1 if the patient is a female, 0 otherwise.As interaction with Travel time and Waiting time
$Over65_i$	=1 if the patient is aged 65 or older, 0 otherwise. As interaction with Travel time and Waiting time
$ExemptFrail_i$	=1 if patient i is exonerated to pay the copayment due to presence of comorbidities and 0 otherwise .As interaction with Travel time and Waiting time
$ExemptInc_i$	=1 if patient i is exonerated from the copayment because of unemployment or low income. As interaction with Travel time and Waiting time

3.5 Results

3.5.1 Descriptive Statistics

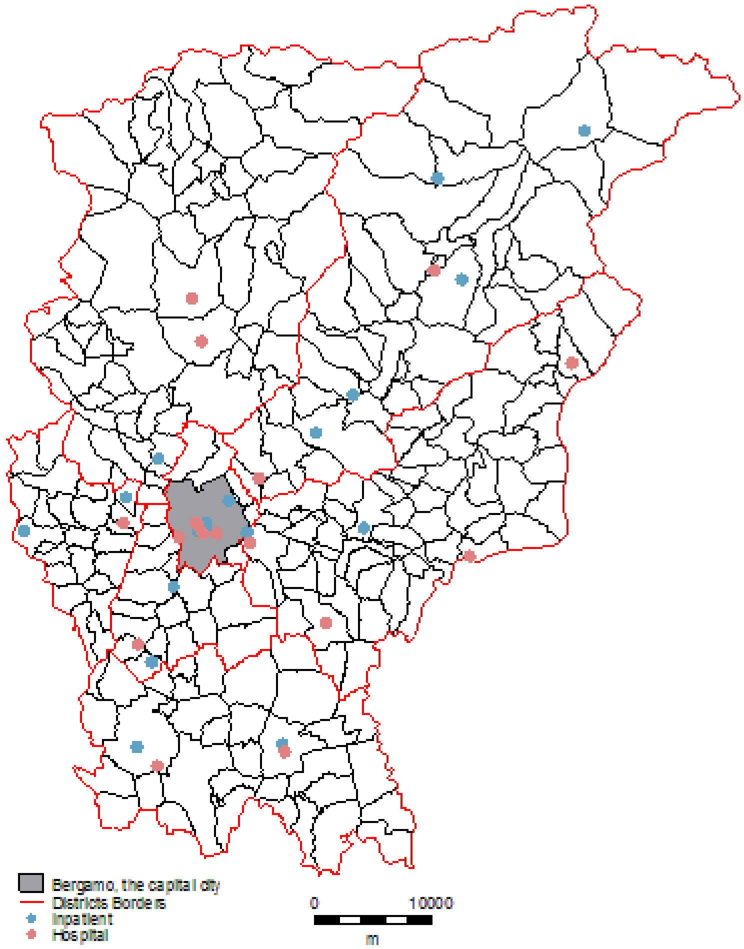
The sample includes 15,913 cardiological visits performed by SSN-licensed providers from January to December 2015. The patients are on average 60.29 years old, and most are female (52.80%). Furthermore, low-income patients account for approximately 16% ($ExemptInc$, n=2509) of the estimation sample, while patients who were exonerated by contributing to the examination expenses due to older age or comorbidities are 48.15% ($ExemptFrail$). Table 3.2 reports that 61% patients have chosen a provider within their district, waiting on average 47 days for a cardiological examination and traveling approximately 15 minutes to reach their chosen provider; the longest travel time in our sample is 87 minutes, with 95% patients traveling for less than 48 minutes. The median number of providers within a driving time of 15 minutes is four; two are hospitals, and the other two provide only outpatient services. This value decreases in the northern parts of the province. Patients living in such areas have only three outpatient care options within a driving time of 15 minutes. As reported in the grey area of Figure 3.1, 9 out of 35 (25.71 %) outpatient care providers within the province are located in Bergamo, the capital city, where hospital concentration is higher (five providers out of nine are hospitals) and where demand represents 35% of the total.

Table 3.2: Descriptive Statistics

Level	**Variable**	**Mean**	**St.Dev.**
Patient Level	Private	1.5413	
	Age	60.2898	21.0956
	Wait	47.3269	59.4749
	Travel	14.8028	9.9253
	Hospital	0.7963	
	District	0.6161	
	Female	0.5284	
	OutSurge	0.5859	
	InSurge	0.2262	
	ExemptInc	0.1577	
	ExemptFrail	0.4815	
Provider Level	Cardiological outpatient volume	954.44	1,110.652
	Total outpatient volume	332,627	570,860
	Share of Private Institutions	0.5714	
	Share of Hospitals	0.4857	
	Providing cardio surgical outpatient services	0.5714	
	Providing cardio surgical inpatient services	0.0857	

Patient demand is concentrated in the city's main public hospital (the Hospital Pope John XXIII , PJXXIII), which provided 1,450 cardiological visits (9.1% of the province's total; see Table 2). Concerning providers' ability to treat complex cases, only three providers are equipped for cardiovascular surgical procedures in the province (8.57% of the total and 22.69% of ambulatory visits), while 19 providers provide also cardiovascular surgery outpatient visits (57.14% of the providers; 58.59% of the patients undergone visits in such institutions) from April (i.e., January, three-month lagged) to December 2015. Overall, 48.57% of providers provide also inpatient care, and 57.13% are private institutions.

Figure 3.1: Geographical distribution of outpatient care providers in the province of Bergamo



3.5.2 Regression Analysis

Table 3.3 reports the results of the mixed logit model (described in Section 4) analyzing the choice sets of all the cardiological visit providers in the province of Bergamo in 2015. The results indicate that patients tend to choose outpatient care providers in close proximity, in line with the findings in studies generally investigating the hospital setting (Sivey, 2012; Tay, 2003; Varkevisser, Geest, and T.Schut, 2012; Beckert, Christensen, and Collyer, 2012). Model (1), the most parsimonious specification, highlights that preferences with respect to travel time are subject to individual-level heterogeneity not captured by the covariates due to the significance of the standard deviation of the coefficient of $Travel$. Such heterogeneity is partially captured in Model (2) by the addition of the interactions of $Travel$ with age age, gender and being exonerated from the copayment due to frailty ($ExemptFrail$) or income ($ExemptInc$) along with the dummy $Hospital$. Model (2) highlights that, after controlling for age, gender and copayment exemption there is still heterogeneity related to unobservables. Indeed, we report a significant coefficient for the random parameter of the coefficient attached to $Travel$, meaning that the individual-level covariates do not completely absorb the variability of travel time preferences related , for instance, to unobserved income, employment and workplace. In terms of copayment exemptions, patients are willing to travel more if they have no out-of-pocket expense. This extra willingness to travel might be because of the reduced consultation cost. Furthermore, patient are willing to travel more to hospitals, which might be perceived as higher-quality institutions or having more amenitites. Our travel time elasticity show that outpatients seem to be more responsive to variations in travel time than are inpatients. Indeed, for a variation in travel time of 1% (0.14 minutes) the associated proportional variation in probability of choice is equal to 3.2% (elasticity equal to –3.2). Such estimate is, in absolute terms, higher than that of inpatients and close to what (Varkevisser, Geest, and Schut, 2010) estimated, indeed a single hospital's travel time elasticity varied from -2.6 to -1.4 for neurosurgical outpatients in the Netherlands.

Moreover, our specifications suggests that outpatients have negative marginal utilities of waiting time. Concerning individual-level heterogeneity of preferences in waiting time, the non significance of the standard deviation of the waiting time coefficient implies that all the heterogeneity is completely explained. This is confirmed when observable characteristics such as Age, Gender and exemption due to frailty or low income. Specifically, females and older adults are willing to wait more, while low-income and those who were cleared from the copayment due to comorbidities are willing to wait less. As for $Travel$, patients are willing to wait more to undergo first cardiological consultations to hospitals. Concerning waiting time elasticities, the 1% increase of waiting time (on average 0.47 days) leads to a decrease of 0.11% of the probability of choice (elasticity equal to -0.11) is consistent with those estimated for inpatients, ranging from -0.24 to -0.07 (Sivey, 2012; Martin et al., 2007).

Provider-wise,the coefficients regarding ownership ($Private$) and specialization in outpatient services ($Hospital$) are positive and significant in both specifications, showing that outpatients are more willing to undergo first cardiological examinations in private providers or hospitals delivering both outpatient and inpatient services. Hospital-specific variable related to knowledge of the cardiovascular system ($InSurge$ and $Outsurge$) and the concordance between district of enrolment (variable $District$) and patient choice are both found to be important factors affecting choice in the outpatient setting and to be consistent across models (1) and (2). Along with the lack of available information concerning outpatient care quality in Italy, the first factor suggests that patients are more likely to choose providers in which they detect signals of high-level cardiovascular expertise, such as the presence of outpatient activity in vascular surgery or the ability to treat complex cardiovascular cases (e.g., the presence of a cardio-surgical unit). The second factor suggests that, when quality information is not available and the skill of the consulting physician is a priori unknown, GPs tend to direct patients towards providers located in their district, as they meet and interact with physicians working there. These findings corroborate past results for the hospital context (Beckert, Christensen, and Collyer, 2012; Varkevisser, Geest, and T.Schut, 2012), confirming that larger providers tend to attract more patients.

Table 3.3: Mixed Logit results

	(1)	(2)
Mean		
OutSurge	0.114***	0.116***
	(0.029)	(0.031)
InSurge	0.257***	0.251***
	(0.043)	(0.043)
Private	0.222***	0.263***
	(0.027)	(0.028)
Volume	0.003***	0.054***
	(0.000)	(0.002)
District	0.861***	0.877***
	(0.025)	(0.025)
Hospital	1.190***	0.965***
	(0.026)	(0.056)
Over65 X Wait		0.006***
		(0.001)
Over65 X Travel		-0.036***
		(0.003)
Female X Wait		0.002*
		(0.001)
Female X Travel		-0.009***
		(0.002)
Hospital X Wait		0.005***
		(0.001)
Hospital X Volume		-0.051***
		(0.002)
Hospital X Travel		0.020***
		(0.002)
ExemptFrail X Travel		0.013***
		(0.003)
ExemptFrail X Wait		-0.006***
		(0.001)
ExemptInc X Travel		0.008*
		(0.003)
ExemptInc X Wait		-0.004***
		(0.001)
Wait	-0.002***	-0.007***
	(0.000)	(0.001)
Travel	-0.130***	-0.127***
	(0.002)	(0.003)
SD		
Wait	0.000	0.000
	(0.001)	(0.001)
Travel	0.055***	0.046***
	(0.003)	(0.003)
Number of providers	35	35
Number of outpatients	15913	15913
AIC	70979	70090
BIC	71090	70324

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 3.4: Robustness check

	(R1)	(R2)
Mean		
OutSurge	0.147***	0.153***
	(0.029)	(0.030)
InSurge	0.424***	0.446***
	(0.044)	(0.045)
Private	0.323***	0.375***
	(0.028)	(0.029)
Volume	0.003***	0.056***
	(0.000)	(0.002)
District2	1.377***	1.519***
	(0.073)	(0.073)
Hospital	1.176***	0.900***
	(0.026)	(0.056)
Over65 X Wait		0.006***
		(0.001)
Over65 X Travel		-0.038***
		(0.003)
Female X Wait		0.001*
		(0.001)
Female X Travel		-0.009***
		(0.002)
Hospital X Wait		0.006***
		(0.001)
Hospital X Volume		-0.053***
		(0.002)
Hospital X Travel		0.019***
		(0.002)
ExemptFrail X Travel		0.014***
		(0.003)
ExemptFrail X Wait		-0.006***
		(0.001)
ExemptInc X Travel		0.008*
		(0.003)
ExemptInc X Wait		-0.003**
		(0.001)
Wait	-0.002***	-0.007***
	(0.000)	(0.001)
Travel	-0.157***	-0.154***
	(0.002)	(0.003)
SD		
Wait	-0.000	0.000
	(0.001)	(0.001)
Travel	0.060***	0.052***
	(0.003)	(0.003)
Number of providers	35	35
Number of outpatients	15913	15913
AIC	71764	70838
BIC	71876	71072

Standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Robustness check

We assess the robustness of the findings above by considering an alternative specification of the variable *District* (Table 3.4). Indeed, GPs may have different preferences in terms of provider to which refer patients. Therefore, we replace *District* with *District*2. This variable has on the numerator the number of patients coming from to the same district as provider j and on the denominator the total number of patients who undergone cardiologic visits in provider j. Such variable would measure the same effect as *District* but allowing a continuous variation in GP preferences. The coefficient attached to *District*2 is positive and significant as its binary alike.
The change of specification of *District* does not lead to variations in significance and sign of the other coefficient estimates. Interestingly, the alternative specification leads to an increase of the coefficients of *Outsurge* and *Private* of respectively 77% (from 0.251 to 0.446) and 42% (from 0.263 to 0.375).This may suggest that a binary specification of the propensity of GPs to refer patients to their district may capture effects of district characteristics in term of presence of private institutions and other cardiological services. For all the other findings the models in Table 3.4 prove to be robust to those reported in Table 3.3.

3.5.3 Policy Simulation

In this section, we illustrate how the results from our choice model (model 2, Table 3.3) of outpatient care can be used to evaluate the impact of policy changes on patient distribution among providers. We conduct a policy simulation involving the closure of a provider in the northeastern part of Bergamo. Such closure have been the subject of local debate over the last few years given the intention of the LHA to reduce healthcare services in mountainous areas to favor the utilization of services provided by institutions located in the center of the province. The provider in question is a hospital located in San Giovanni Bianco, a town in the center of the province's northeastern district with approximately 90,000 inhabitants (approximately 9% of the province's population), many of whom live in the mountainous area, the Brembana Valley. This area is the least covered in term of presence of providers; indeed , patients have two alternatives in the 15 minutes travel time range (median) and wait for a first cardiological examination on average of 37 days and travel 20 minutes. The provider and its LHA district are highlighted in Figure 3.2 respectively in the red circle and in the grey area. Such provider is part of the same public hospital trust who manages PJXXIII hospital, in the city of Bergamo, and the LHA was considering the relocation of some of its services to the PJXXIII hospitalfor the purpose of maintaining an higher quality standard and achieving economies of scale. In this, setting the relocation of outpatient services to the PJXXIII hospital would cause patients residing in the Brembana Valley to opt for the choice of substitute providers, causing a variation in the average travel time for patients and, thus, a variation of welfare. The relocation of outpatient services would also require the two physicians employed at San Giovanni Bianco hospital to reach their workplace at the PJXXIII hospital. For privacy reasons the actual place of residence of such medical specialists is unknown so, assuming that the physicians live in the Province of Bergamo, multiple scenarios will be evaluated as follows:

1. Hypothesize that one of the doctors live in a town
2. Calculate the travel time t_0 from such town to San Giovanni Bianco Hospital
3. Calculate the travel t_1 time from the same town to PJXXIII hospital
4. Obtain the variation in daily travel time by obtaining $\Delta t = t_1 - t_0$

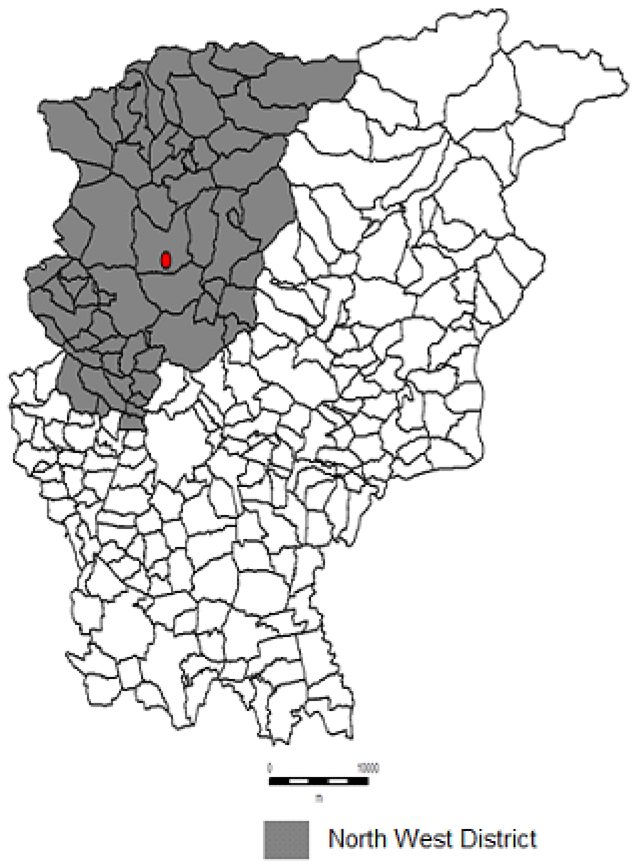
5. Obtain the total variation of travel time by multiplying Δt by N. Where N is 192 (the number of work days from April 1, 2015 to December 31, 2015) if the doctor is full time employed and N is 96 if the doctors is employed on a vertical part time (i.e. works half days of a full time employee)

6. Repeat the previous steps for each town in the Province of Bergamo

7. Repeat the previous steps for each of the two doctors

8. Obtain the combinations of the estimated variations in travel time

Figure 3.2: San Giovanni Bianco Hospital and its District



The policy simulation is performed by first evaluating the predicted choice probabilities , then simulating the closure, and, estimating the absolute demand variations for each provider (i.e., the average additional travel time for each patient in the province after the policy change). The simulation results are shown in Figure 3.3. The blue shading indicates different ranges in the variation of per-capita travel time in minutes in the left panel and variation in the total expected travel time for all patients in the right panel. The red circles indicate the relative change in predicted demand after the simulated closure of San Giovanni Bianco hospital. When the hospital is closed, our model estimates a net total travel time increase of 140 minutes for the whole province, which equals a 0.1% decrease in the total travel time for all patients from the pre-change scenario. Specifically, as shown in both panels of Figure 3.3, this increase is largely attributable to the patients residing San Giovanni Bianco's district who decide to travel to a further provider despite having a closer alternative.

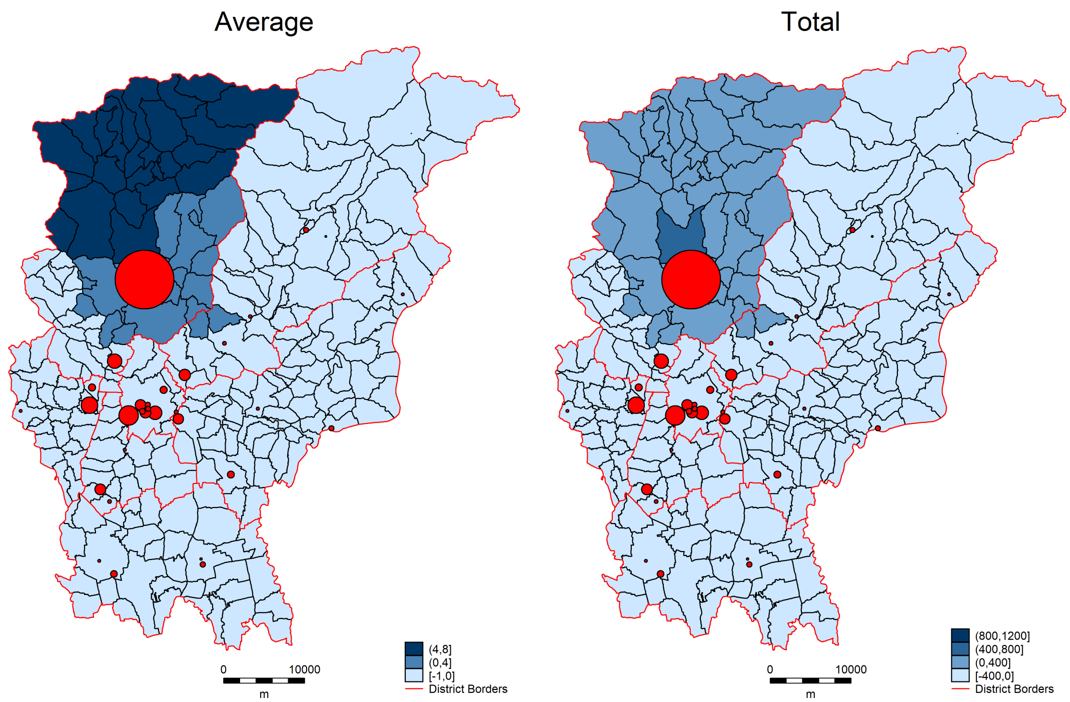


Figure 3.3: Post-policy simulated variation in outpatient provider demand and in expected traveled time

However, 196 of the 329 patients who were originally predicted to choose San Giovanni Bianco hospital are predicted to switch to the closest alternative, while the PJXXIII hospital attracts only 22 patients and would need a reduction of its waiting time (average 7 days) by more than 90% to attract all the patients who were predicted to choose San Giovanni Bianco hospital. Concerning the cardiologists, their variation in total travel time have a higher magnitude than the total impact of the change in patients' mobility due the relocation (a total increase of 140 minutes). Depending on the town of residence the partial contribution of change in physician's mobility ranges from a decrease of 80435 minutes to an increase of 62771 minutes spent traveling by the two medical specialists. In 83% to 84% of the simulated cases the relocation of San Giovanni Bianco's cardiological services implies a net total decrease of traveled time within the Province (Table 3.5).

Scenario	Range	Decrease of total travel time
Both physicians work full time	-80295,+62911	84% of cases
One physician works on vertical part time	-60186,+47218	83% of cases
Both physicians work on vertical part time	-40077,+31525	83.5% of cases

Table 3.5: Post-policy simulated total variation in expected traveled time

3.6 Discussion and conclusion

Despite the importance of understanding the dynamics of patient choice in public health care systems (where providers do not compete on price), the literature has focused on the inpatient setting, leaving unexplored outpatient choice. Indeed, to our knowledge, only two Dutch studies (Varkevisser, Geest, and Schut, 2010; Varkevisser and Geest, 2007a) have explored the outpatient care setting, while two other works give a brief mention to it and estimate the demand functions or the waiting time elasticities (Martin et al., 2007; Sivey, 2012). This study focused on Italy's health service and examined 15,913 first cardiological visits carried out in 2015 in the province of Bergamo to shed light on the mechanisms of outpatients' provider choice using the outpatient record, an overlooked dataset. Our results have implications for both public and publicly licensed private institution who want to plan the outpatient provision. Indeed, our travel time elasticity estimate is about 15 times larger than waiting time elasticity meaning that a 1 % decrease in travel time has the same impact on probability of choice of a 15 % decrease in waiting time. This implies that institutions located in areas where few competitors operate may not be given incentive to reduce waiting times, given that patients are far more sensitive to provider proximity. While, in more competitive areas in terms of presence of health care providers , suppliers have greater incentive to reduce waiting time in order to attract more patients. Furthermore, hospital trusts or local health authorities may consider these results for possible opening or closure of outpatient service facilities. Indeed, as reported in our simulation, the closure of an inpatient service provider with the purpose of attracting patients to a more central hospital may fail because patients would opt for the closest provider unless a considerable waiting time reduction is achieved. Hence, relocation of health services might be effective only if the closed facility is in the nearby of the facility which should attract patients. In turn, such policy turn might cause demand to run above the capacity. Furthermore, our study enriches the current literature on patient choice by shedding light on patient's behavior in a neglected part of public health care: the outpatient service. Apart from corroborating several previous findings in the health care patient choice literature our results suggest that outpatients are more responsive to differences in travel times than inpatients while waiting time elasticities are comparable with previous findings. Besides, as quality information on outpatient care providers is not publicly available in Italy, patients prefer to seek cardiologic consultations from providers with better knowledge and expertise in cardiovascular disciplines and who can treat complex cases. Our analysis suggests that, all other factors being equal, patients prefer to undergo cardiologic visits at providers located in the LHA district of residence, mainly because their referring GP has better knowledge of the specialists working in their district and can therefore advice patients to specialists in its professional network (the district). Further, we contribute to the current knowledge of health care services demand by estimating average waiting time and travel time elasticities in a market setting that includes not only hospitals but also numerous providers specialized in outpatient care. However, our elasticity estimates have to be carefully compared to those available in (Sivey, 2012; Varkevisser, Geest, and Schut, 2010; Riganti, Siciliani, and Fiorio, 2017) due to the different health care service types and patient characteristics involved. Indeed, patients might display different choice behaviors depending on the degree of uncertainty concerning their health status; we assume that outpatient's uncertainty related to a first visit is higher than the uncertainty faced by an inpatient undergoing a treatment, given that the health status is known. Our work come also with some limitations that suggest interesting inputs for future research. The comparison of inpatient and outpatient frameworks presents an avenue for future research; it would be worth empirically comparing inpatient and outpatient care elasticities in the same national framework and within the same medical discipline. Similarly to most of the literature, our study focuses on the public health sector where competition not based on price as they are fixed by regulation. However, many of the Western countries' health care markets are mixed and the public health care sector (with fixed pricing) competes with the private one (with unregulated pricing). Furthermore, this study was limited to the demand of patients residing in the province of Bergamo for providers located in the same province, whereas patients are free to choose health care anywhere in their region (though few do so). As a consequence, patients living near the borders may be more prone to choose services just outside the province than are the patients considered in our analysis.

Chapter 4

Spatial discrete choice modeling in Stata: the spatlogit extension

Abstract

Spatial econometrics have been a growing field of study. Nowadays, there is large body of software package which allows to perform spatial regressions. Although Stata 15 incorporated spatial analysis for continuous independent variables, commands for discrete choice spatial analysis have not been developed yet. In this work I present a new command which allows Stata users to estimate spatial logit models in cross sectional data.

4.1 Introduction

In the last decades, spatial econometrics have been a growing field of study. Moreover, the increase of computational power made possible to estimate spatial models which require the inversion of large matrices or the calculation of multidimensional integrals. Thus, there is growing body of spatial econometrics spatial software packages . Regarding Stata, version 15 of the program developed new spatial software extensions or incorporated many user-written packages regarding spatial econometrics. For instance, Pisati (2001) made available to Stata users commands such as spmap, spatwmat and spreg, which allow to draw detailed maps, to handle large spatial weight matrices or to fit spatial regression models. However, to my knowledge, Stata commands performing spatial regression models (spregress, spxtregress) are currently able to handle models with continuous independent variables, while spatial models having binary independent variables (i.e. equal to 0 or to 1) as the case of discrete choice models can be performed by only by other software. For instance, user written-package "McSpatial" have been made available for R users. Hence, the aim of this work is to present the implementation of a Stata package called splogit which allows users to fit spatial discrete choice in which the dependent variable is spatially autocorrelated. Splogit is based on the on the Generalized Method of Moments (GMM) estimation introduced in Pinkse and Slade (1998)(PS) and on its linearized approximation developed Klier and McMillen (2008)(KM). The paper is organized as follows: the next section provides Stata users a short outline of the econometric framework of splogit, section 3 illustrates the basic syntax and options for splogit, section 4 provides an example of its use and section 5 outlines the future development of this work.

4.2 The econometric setting

4.2.1 Discrete choice analysis with spatial correlation

Let us consider a situation in which a patient faces a binary choice situation in which she may choose to consult or not a specialist. The choice would occur only if her utility U_i is above a certain threshold $\bar{U}_i$. Such utility addictively depends on observables u_i and unobservables, random to the researcher, characteristics ϵ_i. Let us note the actual patient choice as $Y_i = 1(U_i > \bar{U}_i)$ and explicit the observable utility function $u_{ij} = \boldsymbol{X_i\beta}$, where $\boldsymbol{X_i} \in R_p$ is a set of p (continuous or categorical) covariates and $\boldsymbol{\beta}$ is a p-dimensional vector of coefficients to be estimated: this is a random utility framework (McFadden, 1973) in which the researcher observes actual choices and a set of covariates; however, the underlying utility is not observed. A researcher interested in estimating the impact of $\boldsymbol{X}$ and the probability of choice may use a logit model in which the probability of choosing to consult a specialist would be modeled as $P = (Y_i = 1) = P(U_i > \bar{U}_i) = \frac{exp(u_i)}{1+exp(u_i)}$ (Train, 2009). However, this estimation strategy is based on the assumptions that patients' choice and the unobserved component ϵ_{ij} are spatially independent. In contexts such as health, where there is an high degree of asymmetric information, patient choices may be influenced on the choices of their peers living in the nearby; for instance by word of mouth. Model-wise, in an OLS framework such situation would be tackled by allowing the continuous dependent variable for patient i to be correlated with the dependent variable observed for the other decision makers j different from i by using a spatial lag model (Anselin, 2013). In the discrete choice framework this would be akin to allow patient's utility to be correlated over space. Let us introduce the matrix $\boldsymbol{W}$ such that $w_{ij} = f_{ij}/\sum_{j\in J} f_{ij}$ where f_{ij} is a measure of proximity (e.g. inverse distance, inverse squared distance) or contiguity between decision maker i and another decision maker j. In the same fashion as the spatial lag model in an OLS framework patient's i representative utility function would be specified as $u_i = \rho\boldsymbol{W}u + \boldsymbol{X}_i\boldsymbol{\beta} + \epsilon_i = (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}X_i\boldsymbol{\beta} + (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\epsilon_i$ where ρ is an additional parameter to be estimated and measures the extent of the spatial autocorrelation of utility functions. The former model implies autocorrelation as well as heteroschedasticity (Klier and McMillen, 2008; Pinkse and Slade, 1998) given that the variance-covariance matrix $\boldsymbol{V} = E(\boldsymbol{\epsilon\epsilon}^T) = [(\boldsymbol{I} - \rho\boldsymbol{W})^T(\boldsymbol{I} - \rho\boldsymbol{W})]^{-1}$ is not in the form $V = \sigma\boldsymbol{I_n}$ where (I_n) is a suitable identity matrix.

4.2.2 Estimators

The problem arisen in the previous section might be solved by maximum likelihood (ML); however, the ML estimator would be inconsistent in presence of heteroschedasticity and would also be rarely feasible be deployed in large sample because ML would involve the calculation of n dimensional integrals, where n is the number of decision makers (Pinkse, Slade, and Brett, 2002). To overcome this limitation, Pinkse and Slade (1998) introduced an estimator based on the GMM (Hansen, 1982). Let us define the generalized logit residuals $e_i = Y_i - P(Y_i = 1) = Y_i - exp(u_i)/(1 + exp(u_i))$ (Klier and McMillen, 2008) and $n \times k$ matrix of instruments $\boldsymbol{Z}$ with $k \geq p+1$ which can include any set of exogenous variables including $\boldsymbol{X}$. Given the exogeneity of $\boldsymbol{Z}$ would be possible to stack the moment conditions $\boldsymbol{g} = E(\boldsymbol{Z}^T\boldsymbol{e}) = \boldsymbol{0}$ and their sample equivalent $\boldsymbol{g}_n = n^{-1}\boldsymbol{Z}^T\boldsymbol{e}$. With $k \geq p+1$ the number of moment conditions is at least equal to the number of parameters to be estimated, hence parameters $\boldsymbol{\Theta} = (\boldsymbol{\beta}, \rho)$ are consistently estimated minimizing $\boldsymbol{S}_n = \boldsymbol{g_n^T M g_n}$ where $\boldsymbol{M}$ is a positive-definitive matrix which assigns a relative weight to each of the sample moments (Arbia, 2014). An interesting approach to PS methodology is reported in Flores-Lagunes and Schnier (2012) where if $\boldsymbol{M} = \boldsymbol{Z^T Z}$ the GMM procedure reduces to nonlinear two stage least squares and parameters vector $\boldsymbol{\Theta}$ is estimated as follows:

1. assume initial values $\boldsymbol{\Theta}_0$,
2. obtain the gradient terms $\boldsymbol{G}_0$ and generalized residuals $\boldsymbol{e}$,
3. calculate the predicted gradient terms $\hat{\boldsymbol{G}}$ through an OLS of $\boldsymbol{G}_0$ on $\boldsymbol{Z}$,
4. obtain second-stage estimates $\boldsymbol{\Theta}_1 = \boldsymbol{\Theta_0 + (\hat{G}^T \hat{G})^{-1} \hat{G} u_0}$
5. iterate until convergence of $\boldsymbol{\Theta}$.

PS's approach would be computationally burdensome in large datasets where the large matrix $\boldsymbol{I} - \boldsymbol{\rho W}$ is required to be inverted during each interation. Hence, Klier and McMillen (2008) proposed a linearized version of the GMM procedure exploiting the fact that when $\rho = 0$ the gradient term $\boldsymbol{G_\rho} = \partial g_n / \partial \rho \neq 0$. The procedure, as outlined in by the authors is the following:

1. Obtain initial estimates of $\boldsymbol{\beta}_0$ and $\boldsymbol{e}_0$ fitting a logit model (i.e. assume $\rho = 0$)
2. Calculate the initial gradient estimates $\boldsymbol{G_\beta} = P_i(1 - P_i)(\boldsymbol{I} - \rho \boldsymbol{W})^{-1} \boldsymbol{X}^*$ and $\boldsymbol{G}_\rho = P_i(1 - P_i)\boldsymbol{h}_i \boldsymbol{\beta}_0$ where $\boldsymbol{h}_i$ is the vector located at the i-th row of $n \times k$ matrix $\boldsymbol{WX}$ and $\boldsymbol{X}_i^* = \boldsymbol{X}_i / \sqrt{V_{ii}}$
3. Obtain the predicted gradient estimates $\hat{\boldsymbol{G}} = (\hat{\boldsymbol{G}}_{\boldsymbol{\beta}}, \hat{\boldsymbol{G}}_\rho)$ using $\boldsymbol{G_\beta}$ and $\boldsymbol{G}_\rho$as dependent variables and $\boldsymbol{Z}$ as regressors
4. Calculate $\boldsymbol{e}_0 + \boldsymbol{G}_{\boldsymbol{\beta}}^T \boldsymbol{\beta}_0$ and regress it on $\hat{\boldsymbol{G}}$, the obtained coefficients are the desired estimates of $\boldsymbol{\beta}$ and ρ

It must be noted that KM approach would provide a good approximation of ρ only the real underlying parameter it is small. Indeed Klier and McMillen (2008), through Monte Carlo simulation, demonstrate that ρ is consistently estimated only if its real value its larger than 0.1 and smaller than 0.5 in absolute value. If the underlying value of ρ it's outside such range the linearized GMM does not provide accurate estimates and the PS approach must be preferred and, in this case, the linearized estimates could be deployed as initial values. Hence, KM approach is to be preferred when analyzing large datasets that would make the PS approach computationally burdensome or in preliminary analyses.

4.3 The spatlogit command

4.3.1 Syntax and Options

The user is required to ensure that the ordering of the variables is coherent with the ordering of the elements of $\boldsymbol{W}$. The syntax of the command is:

```
spatlogit depvar indepvars [if] [in], wmat(matname) [linearized]
[gmm] [winstr(varlist)] [instr(varlist)] predict(varname).
```

wmat(matname)	Required option. The spatial weight matrix $\boldsymbol{W}$ is needed for the estimation of the model.
linearized	The default option. Fit a KM linearized version of Pinkse and Slade's spatial logit estimator
gmm	Fit a Generalized Method of Moments spatial lag logit model (PS). If gmm is specified the estimation procedures uses the linearized version estimates as starting values.
winstr	List of instruments to be multiplied by the spatial weight matrix $\boldsymbol{W}$
instr	List of instruments not to be multiplied multiplied by the spatial weight matrix $\boldsymbol{W}$. Options instr and winstr may be specified togheter. The user is required to specify winstr or instr
predict(varname)	Generate varname, a variable containing the predicted probabilities calculated as $p = exp[(\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\boldsymbol{X\beta}]/(1 + exp[(\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\boldsymbol{X\beta})]$

4.4 Examples

The dataset is artificially generated with $\rho = 0.4$ and includes 240 individuals with observed covariates are $\boldsymbol{x_1} \sim Uniform(10, 40)$,$\boldsymbol{x_2} \sim Uniform(0, 25)$ and $\boldsymbol{x_3} \sim Uniform(0, 30)$. The spatial weights matrix $\boldsymbol{W}$ is based on the row standardization of the distance matrix of the towns in the Province of Bergamo, Italy with $w_{ij} = 1(d_{ij} < 10)$ and d_{ij} being the fastest driving time between town i and town j in minutes according to Google Maps. Unobserved utilities were artificially created as $u_i = (\boldsymbol{I} - \rho\boldsymbol{W})(0.005 + 0.5 * x1 + 2x_2 + x_3 + \epsilon_i)$ where $\epsilon_i \sim N(0, 1)$ and $\rho = 0.4$. Observed choices are $y_i = 1(u_i > \bar{u})$ where $\bar{u}$ is the 50th percentile of the distribution of u_i The Stata code for importing matrix $\boldsymbol{W}$ and generating the artificial dataset is the following:

```
**importing matrix W
import delimited wmat.csv
mkmat *, matrix(W)
set seed  18042017
mata:
mata clear
W=st_matrix("W")
n = rows(W)
rho = .4
// create x1,x2 and x3 from random uniform distributions
x1 = (10:+30*runiform(n,1))
x2=(25*runiform(n,1))
x3=(30*runiform(n,1))
//create the utility variable
u=invsym(I(n)-rho*W)* (.005:+.5*x1+x3+2*x2+rnormal(n,1,0,1))
st_addvar("float", "x1")   // create the variables in Stata
st_addvar("double", "x2")
st_addvar("double", "x3")
st_addobs(n - st_nobs())  // add any observations in Stata when necessary
st_store(.,1,"x1",x1)         // store matrices x1, x2, x3 and u in Stata
st_store(.,2,"x2",x2)
st_store(.,3,"x3",x3)
st_addvar("double", "u")      // create the variable in Stata
st_addobs(n - st_nobs())
st_store(.,4,"u",u)         // store the matrix in Stata
end
quie sum u, detail
// generating binary choice variable
gen y=u>r(p50)
```

The chosen instruments for obtaining the estimates of the impact of $\boldsymbol{X} = (\boldsymbol{x_1}, \boldsymbol{x_2}, \boldsymbol{x_3})$ on y are $(\boldsymbol{X}, \boldsymbol{WX})$ as suggested in Klier and McMillen (2008). In Figure 4.1 the Stata output for the linearized logit is presented, in the top panel initial ordinary logit estimates are displayed, such estimates are then used as initial values for the linearized spatial model (bottom panel) which results in $\hat{\rho} = 0.289$ and in $\hat{\boldsymbol{\beta}} = (0.055, 0.227, 0.113, -6.039)$. The confidence interval for $\hat{\rho}$ includes its real value $\rho = 0.4$

```
. spatlogit y x1 x2 x3, wmat(W) winstr(x1 x2 x3) instr(x1 x2 x3)
STARTING VALUES

Iteration 0:   log likelihood = -166.35532
Iteration 1:   log likelihood = -106.77005
Iteration 2:   log likelihood = -106.18666
Iteration 3:   log likelihood =  -106.1863
Iteration 4:   log likelihood =  -106.1863

Logistic regression                               Number of obs   =        240
                                                  LR chi2(3)      =     120.34
                                                  Prob > chi2     =     0.0000
Log likelihood =  -106.1863                       Pseudo R2       =     0.3617

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .0545584   .0204891     2.66   0.008     .0144006    .0947163
          x2 |   .2295219   .0303242     7.57   0.000     .1700876    .2889563
          x3 |    .114734   .0222018     5.17   0.000     .0712193    .1582487
       _cons |  -6.092863   .8989783    -6.78   0.000    -7.854828   -4.330898
------------------------------------------------------------------------------
LINEARIZED LOGIT
------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .0545672   .0209575     2.60   0.009     .0134914    .0956431
          x2 |   .2267627    .031949     7.10   0.000     .1641437    .2893817
          x3 |   .1125605   .0229412     4.91   0.000     .0675965    .1575245
       _cons |  -6.039383   .9060474    -6.67   0.000    -7.815203   -4.263562
         rho |   .2895145   .3228638     0.90   0.370     -.343287     .922316
------------------------------------------------------------------------------
```

Figure 4.1: Stata output for linearized spatial logit

In the estimation of the GMM spatial logit the linearized spatial logit estimates $\hat{\rho} = 0.289$ and $\hat{\boldsymbol{\beta}} = (0.055, 0.227, 0.113, -6.039)$ are used as starting values. After six iteration the the estimated parameter are $\hat{\rho}_{GMM} = 0.278$ and $\hat{\boldsymbol{\beta}}_{GMM} = (0.054, 0.236, 0.116, -6.191)$. Stata output for GMM spatial logit is reported in Figure 4.2.

```
. spatlogit y x1 x2 x3, wmat(W) winstr(x1 x2 x3) instr(x1 x2 x3) gmm
STARTING VALUES

Iteration 0:   log likelihood = -166.35532
Iteration 1:   log likelihood = -106.77005
Iteration 2:   log likelihood = -106.18666
Iteration 3:   log likelihood =  -106.1863
Iteration 4:   log likelihood =  -106.1863

Logistic regression                             Number of obs     =        240
                                                LR chi2(3)        =     120.34
                                                Prob > chi2       =     0.0000
Log likelihood =  -106.1863                     Pseudo R2         =     0.3617

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .0545584   .0204891     2.66   0.008     .0144006    .0947163
          x2 |   .2295219   .0303242     7.57   0.000     .1700876    .2889563
          x3 |    .114734   .0222018     5.17   0.000     .0712193    .1582487
       _cons |  -6.092863   .8989783    -6.78   0.000    -7.854828   -4.330898
------------------------------------------------------------------------------
LINEARIZED LOGIT
------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .0545672   .0209575     2.60   0.009     .0134914    .0956431
          x2 |   .2267627    .031949     7.10   0.000     .1641437    .2893817
          x3 |   .1125605   .0229412     4.91   0.000     .0675965    .1575245
       _cons |  -6.039383   .9060474    -6.67   0.000    -7.815203   -4.263562
         rho |   .2895145   .3228638     0.90   0.370     -.343287     .922316
------------------------------------------------------------------------------
GMM
Iteration        6
------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .0541274   .0205676     2.63   0.008     .0138156    .0944393
          x2 |   .2360275   .0294568     8.01   0.000     .1782932    .2937617
          x3 |   .1157887   .0211586     5.47   0.000     .0743185    .1572589
       _cons |  -6.190671    .812591    -7.62   0.000     -7.78332   -4.598021
         rho |   .2788654     .28679     0.97   0.331    -.2832326    .8409635
------------------------------------------------------------------------------
```

Figure 4.2: Stata output for GMM spatial logit

4.5 Conclusion

This work discussed the introduction of a new Stata package which allows to estimate logit models for spatially lagged utility functions. Concerning the linearized version of the spatial logit model the results are the same as those obtained by using the R command splogit (Figure 4.3). Furthermore, the estimates obtained from my Stata development of the spatial GMM logit are very similar to those resulting from gmmlogit in R (Figure 4.4, absolute difference in $\hat{\rho} = 0.00142$ or 0.5%). Such difference might be explained by different algorithm for matrix inverters between Stata and R and also by different convergence criteria between gmmlogit and spatlogit's gmm estimator (gmmlogit converged at the 7th iteration and spatlogit converged at the 6th). However, this package does not come without limitations: first, at the current state splogit cannot handle datasets with repeated observation per geographical unit (i.e. panel data, pooled cross sections); second, integration with current Stata spatial analysis command suite is not yet available. These aspect are the main future implications of this work. Further, the expected development of this package is to be part of a software extension suite which grants the researcher the possibility to fit both the linearized and the GMM version of spatial probit models along with multinomial specifications.

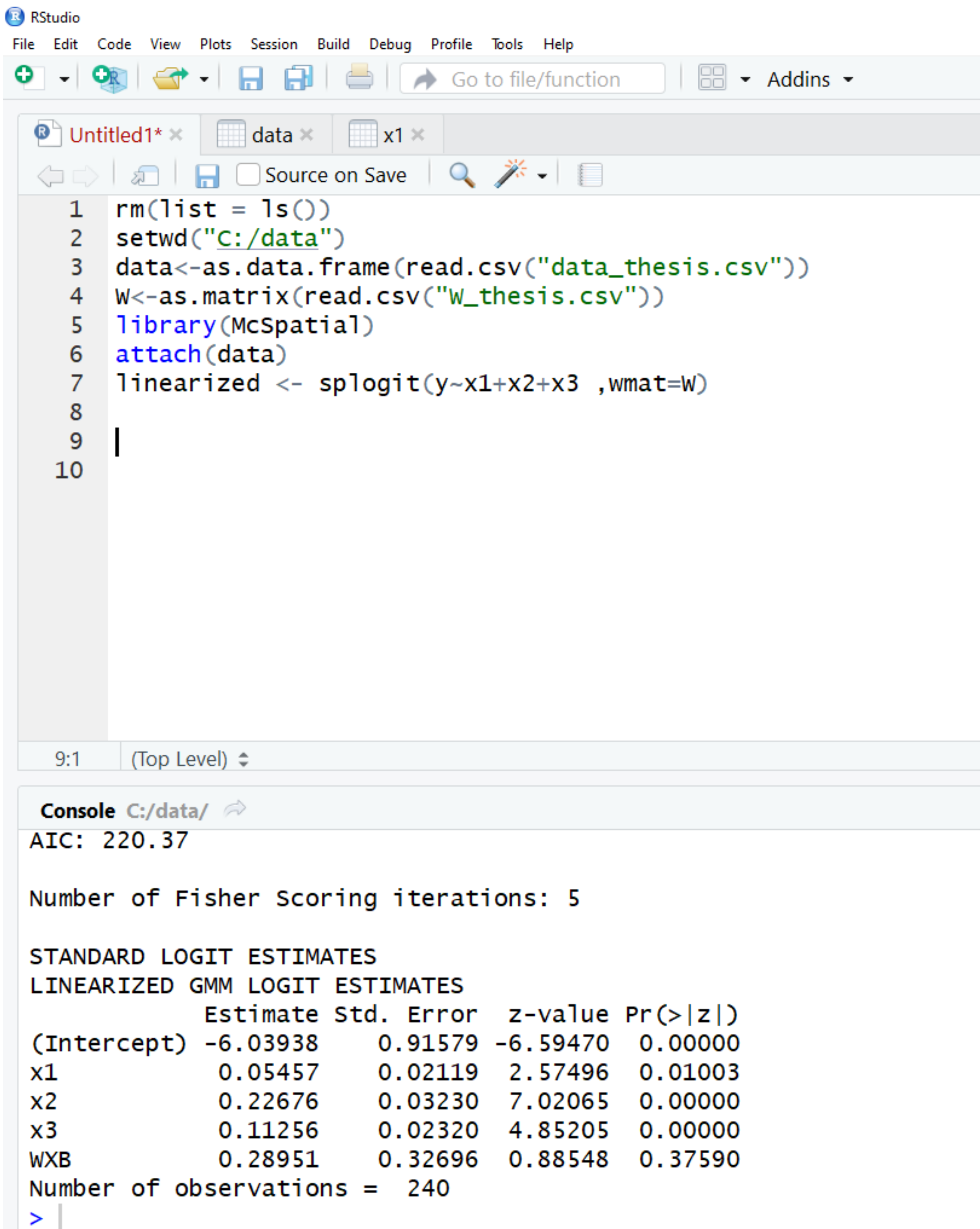


Figure 4.3: R output for linearized spatial logit

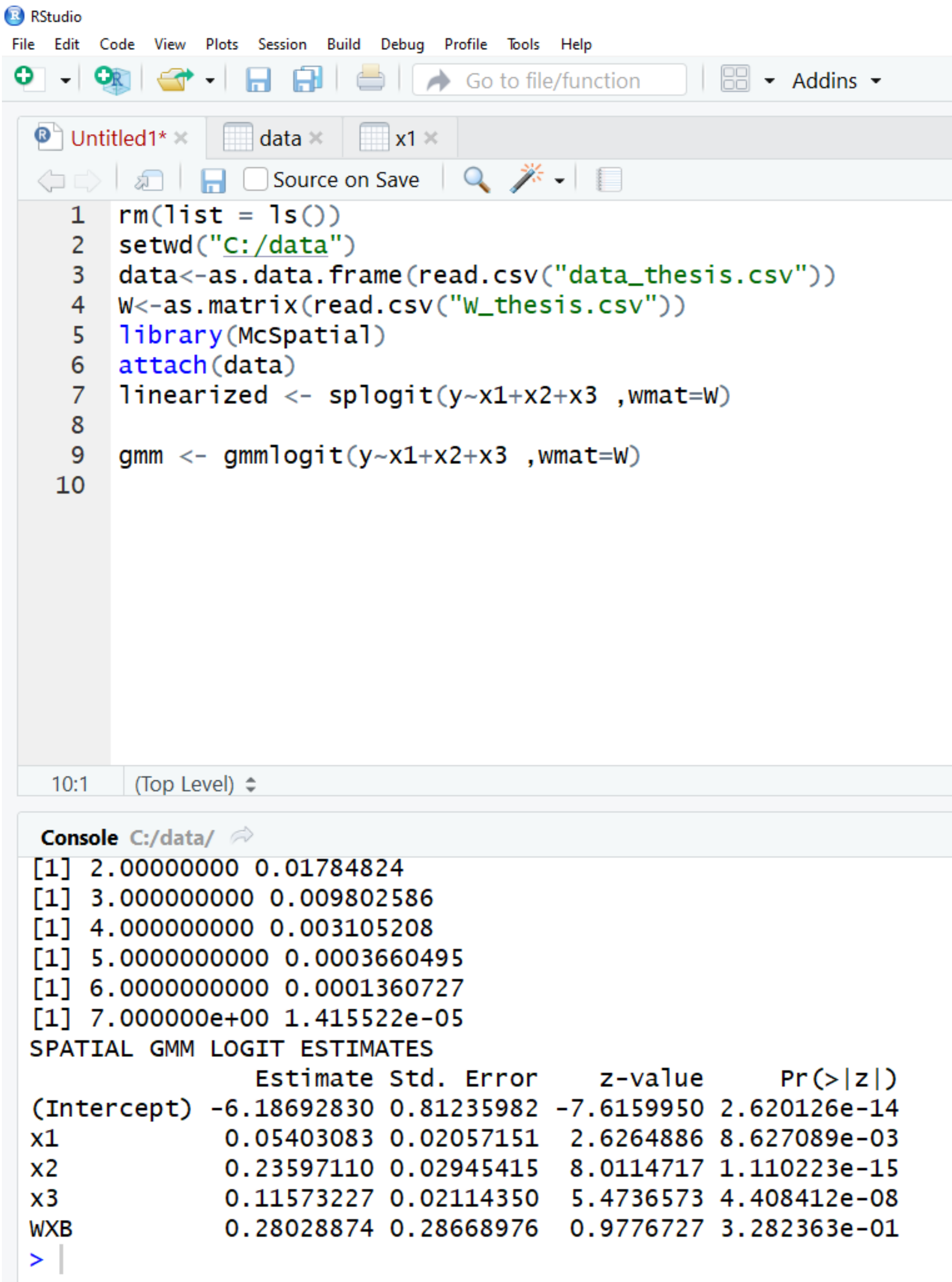


Figure 4.4: R output for GMM spatial logit

4.6 Stata code for splogit

```
set trace off
cap mata:  mata drop _iter()
cap mata: mata drop _maximize()
cap pro drop spatlogit
cap pro drop _linearized
/********* GMM LOGIT ROUTINE *********/
mata:
real matrix _iter(real matrix y, real matrix  x, real matrix b0,real scalar rho,real matrix W, s
{
real matrix v,V,xb, xstar,p,u0,lambda, du,g_rho,G,g_b,Z,G_hat, delta_b, H, sigma

i=1
_has_converged=0
Z=x,W*x
 while(_has_converged<1)
{
printf("Iteration %9.0f \n",i)
n=rows(W)
IpW=(I(n)-rho*W)
v=luinv(IpW)
//variance covariance matrix
V=invsym(IpW'*IpW)
// Vii
sigma=sqrt(diagonal(V))
// if (model=="error") xstar=x:/sigma
// calculation of x*
if (model=="lag") xstar=v*x:/sigma
xb=xstar*b0'
p=exp(xb):/(J(n,1,1)+exp(xb))
u0=y-p
lambda=diagonal(V*(W+W'-2*rho*W*W')*V)

du=p:*(1:-p)
// gradient of P wrt to betas
g_b=du:*xstar
/* if (model=="error") g_rho=-du:*xb:/(2*sigma:^2):*lambda segno g_rho + o -?*/
if (model=="lag") {
H=v*W*xstar
//derivative of P wrt rho
g_rho=du:*(H*b0'-lambda:*xb:/(2*sigma:^2))
}
//full gradient
G=g_b,g_rho
/*calculation of G_hat (predicted gradient) as prediction of
```

```
a regression of G on Z */
G_hat=Z*invsym(Z'*Z)*Z'*G
/* variation of beta wrt to current beta value, the coeffcients of a regression
 of residuals on G_hat*/

delta_b=invsym(G_hat'*G_hat)*G_hat'*u0
b1=(b0,rho)+delta_b'
if (missing(b1)) {
printf("matrix has missing values")
_has_converged=1
_error(144)
}
b0=b1[1,1..(cols(b1)-1)]
rho=b1[1,cols(b1)]
//CONVERGENCE CRITERION, algorithm converges if max absolute variation of
beta between iterations is <0.0001 */
_has_converged=max(abs(delta_b))<0.0001
i=i+1
}

// calculation of standard errors (eq. 3 in Klier McMillen 2008)
sandwich=J(cols(G_hat),cols(G_hat),0)
for (i=1; i<=rows(G_hat); i++)
{
G_i=G_hat[i, 1..cols(G_hat)]
sandwich=sandwich+u0[i,1]^2*G_i'*G_i
}
var_b=invsym(G_hat'*G_hat)*sandwich*invsym(G_hat'*G_hat)

b=(b0, rho) \ var_b
return(b)

}
end
/********* MAIN PROGRAM, CALLS LINEARIZED AND GMM LOGIT *********/
program define spatlogit, eclass
syntax varlist(min=2 numeric) [if] [in] , wmat(string) ///
[winstr(varlist)] [instr(varlist)] [LINearized] [gmm] [Predict(string)]
marksample _touse
gettoken y varlist : varlist
local x `varlist'

tempname b V
cap confirm matrix `wmat'
if _rc {
di as error "matrix `w' not found or not defined"
```

```
exit _rc
}
if ("`linearized'`gmm'"=="") local linearized linearized



tempname _wz _z W_inst
// require the user to insert instruments Z
cap assert "`winstr'`instr'"!=""
if _rc {
di as error "please specify winstr and/or instr"
exit 198
}
else {
// check conformability of instruments
if "`winstr'"!=""{
mkmat `winstr', matrix(`_wz')
cap matrix `W_inst'=`wmat'*`_wz'
if _rc {
di as error "conformability error between `wmat' and instrument `winstr'"
exit _rc
}
}
if "`instr'"!=""  mkmat `instr', matrix(`_z')
if ("`instr'"!="" & "`winstr'"!="") matrix `_z'=`_z', `W_inst'
else if "`instr'"=="" matrix `_z'=`W_inst'
cap assert colsof(`_z')>`: word count `x''
// perform linearized model
if !_rc _linearized `y' `x' if `_touse', w(`wmat') instr(`_z')
else {
di as error "please specify more instruments"
exit _rc
}
matrix `b'=r(b)
matrix `V'=r(V)
}
//perform GMM model if required by the user
if ("`gmm'"!="") {
di "GMM"
mata: MODEL="lag"
mata: W=st_matrix("W")
mata: n=rows(W)
mata: x=st_data(.,"`x'"), J(n,1,1)
mata: y=st_data(.,"`y'")
```

```
mata: b0=st_matrix("e(b)")
mata: rho0=b0[1,cols(b0)]
mata: b0=b0[1,1..cols(b0)-1]

tempname b1
mata: st_matrix("‘b1’",_iter(y,x,b0, rho0, W,"lag"))
matrix colnames ‘b1’=‘x’ _cons rho
matrix ‘b’=‘b1’[1,1..colsof(‘b1’)]
matrix ‘V’=‘b1’[2..rowsof(‘b1’),1..colsof(‘b1’)]
matrix rownames ‘V’= ‘x’ _cons rho
matrix colnames ‘V’= ‘x’ _cons rho
quie count if ‘_touse’
 ereturn post ‘b’ ‘V’ , obs(‘=r(N)’) depname(‘y’) esample(‘_touse’) noclear
ereturn display


}
if ("‘predict’")!="" {
mata: beta_hat=st_matrix("e(b)")
mata: rho=beta_hat[1, cols(beta_hat)]
mata: beta_hat=beta_hat[1,1..cols(beta_hat)-1]
mata:  U_hat=luinv(I(rows(W))-rho*W)*x*beta_hat’
mata: U_hat= invlogit(U_hat)
mata: st_addvar("float", "‘predict’")
mata: st_store(., "‘predict’", U_hat)

}




end

/********* LINEARIZED LOGIT ROUTINE *********/
cap pro drop _linearized
program define _linearized, rclass
syntax varlist(min=2 numeric) [if] [in] , Weight_mat(string) [instr(string)]


gettoken y varlist : varlist
local x ‘varlist’
tempname b X Z G1 G2 Xb u u0 b0 W GRAD G
tempvar p xb grad _u0
display "STARTING VALUES"
// logit regression as starting variable for linearized logit
logit ‘y’ ‘x’ ‘if’
```

```
matrix `b0'=e(b)


quie predict `p' if e(sample)
quie predict `xb' if e(sample), xb

gen `grad'=`p'*(1-`p') if e(sample)
matrix `W'=`weight_mat'
// generalized residuals
gen `_u0'=`y'-`p' if e(sample)
// make matrices with variables
mkmat `_u0' if e(sample), matrix(`u0')
mkmat `xb' if e(sample), matrix(`Xb')
mkmat `x' if e(sample), matrix(`X')
mkmat `grad' if e(sample), matrix(`GRAD')
matrix `Z'=`instr',J(rowsof(`X'),1,1)
matrix `X'=`X',J(rowsof(`X'),1,1)
// gradient of P wrt to Beta
matrix `G1'=diag(`GRAD')*`X'
// gradient of P wrt to rho
matrix `G2'=hadamard(`GRAD',(`W'*`Xb'))
matrix `G'=`G1',`G2'
matrix `u'=`u0'+`G1' *`b0''
tempname G_h
//calculate G_hat as a prediction of the regression of G on Z
matrix `G_h'= `Z' * invsym(`Z''*`Z')* `Z'' *`G'
matrix colnames `G_h' =  `x' _cons rho
//regress G_hat on residuals
matrix `b'=(invsym(`G_h''*`G_h')*`G_h''*`u')
tempname e sse sq_e h sandwich V H
matrix `e'=`u'-`G_h'*`b'
//squared residuals
matrix `sq_e'=hadamard(`e',`e')
// sum of squared residuals
matrix `sse'=`e'*`e''
matrix `h'=vecdiag(`G_h'*invsym(`G_h''*`G_h')*`G_h'')'
matrix `h'= vecdiag( `G_h'*invsym(`G_h''*`G_h')*`G_h'' )'

forval i=1/`=rowsof(`h')' {
matrix `sandwich'=nullmat(`sandwich')\ (`sq_e'[`i',1] / (1-`h'[`i',1]) )

}

display "LINEARIZED LOGIT"
/*
matrix sandwich=`sandwich'
```

```
matrix G_h=‘G_h’
matrix V=invsym(‘G_h’’*‘G_h’)*‘G_h’’*diag(‘sandwich’)*‘G_h’*invsym(‘G_h’’*‘G_h’)
*/
matrix ‘V’=invsym(‘G_h’’*‘G_h’)*‘G_h’’*diag(‘sandwich’)*‘G_h’*invsym(‘G_h’’*‘G_h’)
matrix ‘b’=‘b’’

 ereturn post ‘b’ ‘V’ , obs(‘=r(N)’) depname(‘y’)
ereturn display

end
```

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