UNIVERSIDADE CATÓLICA PORTUGUESA

The Impact of Traveling and Waiting Times in Health Care Emergency Service Choice

An Econometric Approach

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Abstract

This study aims at estimating the effect of traveling and waiting times on patients' choice of emergency care provider. In a model with no outside option, patients choose to demand emergency care from one of two similar hospitals. Using data from two Portuguese public hospitals, a conditional logit model is estimated. Two measures of waiting times are considered: the waiting time between admission and triage and the waiting time between triage and the first medical observation. A negative, statistically significant, impact of traveling time and waiting time between triage and the first medical observation on the probability of choosing a given hospital is found. The magnitude of the effect of waiting time, however, is close to zero. The estimated marginal effect suggests that a supply-induced 30-minutes increase in waiting time reduces, all else equal, the probability of choosing a given hospital by 0.009 percentage points. An increase of the same magnitude in traveling time reduces, all else equal, the probability of utilization by 5.841. Although the data does not allow for the estimation of consumer surplus, and given that the estimated effect captures only the impact of changes in waiting times resulting from supply side decisions, it is plausible to admit their effect on patient welfare would be small.

Keywords: Waiting Time, Traveling Time, Health Care.

Resumo

Este estudo procura estimar o efeito do tempo de deslocação e de espera na escolha de serviços de urgência por parte dos pacientes. Num modelo sem uma *outside option*, os utentes escolhem entre dois serviços de urgência de dois hospitais semelhantes. Utilizando dados de dois hospitais públicos Portugueses, um modelo *logit* condicional é estimado. Duas medidas de tempo de espera são consideradas: o tempo de espera entre a admissão e triagem e o tempo de espera entre a triagem e a primeira observação. Os resultados sugerem a existência de um efeito negativo, estatisticamente significativo, dos tempos de deslocação e de espera entre a triagem e a primeira observação na probabilidade de um paciente escolher determinado hospital. No entanto, a magnitude do efeito dos tempos de espera é próximo de zero. O efeito marginal estimado de um aumento de 30 minutos induzido pelo lado da oferta na probabilidade de escolher um dado hospital é, tudo o resto constante, -0,009 pontos percentuais. Um aumento de igual magnitude no tempo de deslocação reduz, tudo o resto constante, aquela probabilidade em 5,481 pontos percentuais. Apesar de os dados não permitirem a estimação do excedente do consumidor, e dado que o efeito estimado captura apenas o impacto de variações nos tempos de espera causados por decisões de oferta, é razoável concluir que estas não tenham um impacto significativo no bem-estar dos pacientes no caso dos serviços de urgência.

Palavras-chave: Tempo de Espera, Tempo de Deslocação, Cuidados de Saúde.

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1. Introduction

Health care is consensually perceived as being distinct from other goods, mainly because of its ethical implications, which makes the evaluation of health care provision an extremely delicate matter. In a seminal contribution, Arrow (1963) addressed a number of aspects that distinguish the market for health care from the markets for other commodities

One of the distinctive features of health care markets is the role of the monetary price consumers face. The presence of insurance and/or the existence of tax-funded national health services—as is the case of several western countries—usually dampen the monetary costs consumers incur at the time of purchase. Therefore, the instrument that is used in most markets to curb demand—the monetary price—is often unavailable to providers and policy makers in health care markets.[1] This gives rise to an increase in the relative importance of non-monetary costs, among which time plays a predominant role, as determinants of demand and as a public policy tools.

Waiting times—broadly defined as the period of time between the moment in which patients, or an agent on their behalf, like a physician, demand the medical good and the moment in which it is supplied—affect treatment outcomes and efficiency, thus, shaping investment and capacity decisions. In the case of emergency care and due to its short-term nature, such effect is often amplified.

Whether waiting times are viewed as a result of insufficient capacity, or an instrument that aligns supply and demand, hence bringing health care markets to an equilibrium like prices do in markets for other private goods, they are highly likely to enter patients' utility functions.[2] Economic theory

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[1] For example, Duarte (2012), using data for Chile, finds demand elasticities for acute health care close to zero.

2 See, for exemple, Siciliani (2008) and Brekke et al. (2008) for dynamic and static discussions along those lines.

predicts that an increase in the waiting time in health care emergency services has a negative impact on the demand for these services and, hence, in the welfare of users.

The main purpose of this study is to analyze the effects of provider specific factors (among which travel and waiting time are deemed of special interest) on patient emergency care choice. Using data from two major general hospitals in the city of Porto, Portugal, a discrete-choice demand model for emergency services is estimated by Maximum Likelihood. The results show that waiting times have a negative and significant effect on the probability of a given hospital being chosen, but very modest in size. The estimated marginal effect suggests that a supply-induced 30-minute increase in waiting time reduces, all else equal, the probability of choosing a given hospital by 0.009 percentage points. As far as the traveling time is concerned, the estimated marginal effect implies a 5.581 decrease in the probability of choosing a given hospital, all else equal.

The remaining of this study is organized as follows. Section 2 reviews the related literature, devoting particular attention to the Portuguese case. Sections 3 and 4 present, respectively, the random utility choice framework and the estimation procedure. Section 5 offers an institutional description of public health care provision in Portugal. Section 6 presents the dataset and conceptually discusses the construction of the explanatory variables in the econometric model, and provides first attempt to understand the link between waiting times and choice. Section 7 reports the results and accesses the estimates. Section 8 debated policy implications. Finally, Section 9 concludes.

2. Literature Review

Demand for health care and time costs are the subject of a significant body of both theoretical and empirical literature.

The idea that in order to produce a set of commodities individuals must combine inputs of market goods and their own time was first purposed by Becker (1965). He introduced time consumed as a cost to the individual and presented a theory of the allocation of time between different activities. This framework was then applied to the health care market by Grossman (1972). In a model of the demand for health and medical care, patients produce health by combining two inputs: time and medical care. Medical care consumption is, thus, associated with both a monetary cost—the price of the medical good—and a nonmonetary one—time.

In the presence of insurance, the relative importance of the monetary cost is dampened. Since health care consumption requires a substantial expense in terms of time, the lower the coinsurance, the lower the monetary price patients have to bear, which implies that the time price becomes relatively more important. This idea was explored by Newhouse and Phelps (1974), who investigated the link between insurance and the relative importance of the time price and found empirical evidence that lower coinsurance rates were indeed associated with higher time elasticities of demand. Another important contribution may be found in the work of Cauley (1987), which corroborates the findings of Newhouse and Phelps (1974). His results suggest that increases in the time requirement and in the monetary price have a negative effect on demand, which is consistent with *a priori* expectations. Further, he also suggested that the time price is a large fraction of the total cost patients incur when seeking treatment, which indicates that patients normally place a high marginal value on the time required in health care consumption.

Acton (1976) expanded this idea further, by dividing the total cost of health care into monetary price, the amount of time between arriving at the provider office and being treated—waiting time—, and the travelling time.[3] He studied the effects of each of these costs on the demand for health care. The main purpose of the study was to find if time prices would be an appropriate mechanism for controlling demand as the monetary price decreased in the presence of insurance.[4] Using a utility maximization model, he concluded that nonmonetary factors, as time, act as prices in discouraging demand. The results for two separate samples yielded negative own-elasticities of demand with respect to both travelling and waiting times for outpatient departments and for private physician visits, supporting the idea that time is a suitable instrument for controlling demand. The point estimates for the elasticities all smaller than one in absolute value suggest that the demand for health care at those types of providers is inelastic with respect to time, though.

In line with Acton (1976) is the later work of Martínez-Garcia et al. (1998). Their formulation is akin to that of Acton (1976), since it considers the opportunity cost of traveling and waiting times in the budget constraint as if they were monetary prices. They analyze the elements that influence patients' choice between provider alternatives in the Spanish health system, placing special emphasis on traveling and waiting times. The results revealed that emergency services demand is very sensitive to time costs. In fact, they concluded that the demand for emergency services is more elastic than the

[3] In an attempt to study the impact of travelling time in determining the demand for medical services in New York City, Acton (1975) used the travelling distance as a proxy for the travelling time.

[4] Brekke et al. (2008) present a model of hospital competition in which hospitals avoid treating unprofitable patients by increasing waiting times.
Blundell and Windmeijer (2000) present a model in which waiting time acts as a cost to treatment and is sufficient to reduce demand to equal supply – if there is an increase in demand, waiting times will increase, causing some individuals to drop out, which will reduce the waiting times.

demand for specialist services and the demand for appointments with general practitioners.

The set of approaches addressed so far might also be applied to the case of the Portuguese National Health Service, under which copayments amount only to a very small part of true service cost and, therefore, where the relative importance of the monetary cost is reduced. In fact, some attention has been given to the link between increases in copayments and health care demand in Portugal, with the evidence suggesting that the former are somewhat ineffective in controlling the latter. Using data from an undisclosed Lisbon hospital, Afonso et al. (2013) concluded that copayments are not an important barrier in the access to health care, although they discourage the utilization of emergency care by patients with milder health conditions.[5] Almeida and Ramos (2015) analyzed the effect of an increase in both direct and indirect costs on the demand for emergency services in Portugal and reported that emergency services demand was not significantly affected by the increase in copayments, while the change in transport regulation had a substantial impact on demand. Their results support the view that indirect costs may be more important than direct costs in determining healthcare when copayments are small and exemption schemes are available.

For Portugal there is no equivalent to the work of Acton (1976), associating demand for health care and the total time cost. Actual distance is alternatively used as a proxy for traveling time, and waiting times as defined above are not considered. Examples of this approach may be found in Santana (1996) and Oliveira (2004). The former attempts to evaluate whether hospital utilization is decreasing in the distance between the patient's residence and the hospital.

[5] These findings were corroborated by a study on the impact of the 2012 increase in user fees in the Portuguese National Health System conducted by Entidade Reguladora da Saúde, the Portuguese Health Regulator. According to the report, the increase in user fees were accompanied by a reduction in the utilization of both exempt and non-exempt patients, ruling out the former as the cause of the latter. There was, however, an increase in the share of acute cases in the total number of emergency episodes, which suggests that emergency services demand by low severity patients was hindered.

Her results are consistent with Acton's (1975) findings since an increase in distance has a negative influence on demand. She also found that this influence is greater for emergency services visits, which is in line with the work of Martínez-Garcia et al. (1998). The latter develops a demand model for hospital care in which demand is a function of the distance the patient has to travel to get to the hospital. The empirical analysis shows that patients that are located further away from the hospital have a lower probability of utilization, supporting the rationale that the distance a patient has to travel, and hence the traveling time, and the demand for medical services are negatively correlated.

Contrary evidence is presented by Lourenço and Ferreira (2005), whose findings indicate that time is not a determinant of demand for public health centers in Portugal. Lourenço and Ferreira's (2005) findings refute the argument that time costs are relevant in determining demand. They concluded that utilization is highly inelastic to the total time spent at the health care center and that the elasticity of demand with respect to the traveling time is actually positive. They argue that these results can be explained by the characteristics of the health center users and the health centers distribution across the country.

3. Theoretical Framework

In order to answer the research question I follow Matinez-Garcia et al. (1998). I model patient choice between two alternatives—emergency care from Hospital a or Hospital b. The utility derived from getting treatment at either hospital is not observed, only the actual choice is. Thus, the observed choice between the two hospitals reveals which of the alternatives provides greater utility. In other words, the observed outcome reveals how the patient ranks the two alternatives. Both the patient's and the hospitals' observable and unobservable characteristics affect the utility derived from emergency care consumption at each one of the hospitals and, accordingly, influence the choice between them.

Let U_{ia} and U_{ib} represent patient i's utility from choosing hospital a and hospital b, respectively:

$$U_{ia} = \boldsymbol{z}'_{ia}\boldsymbol{\theta} + \varepsilon_{ia}, \tag{1}$$

$$U_{ib} = \boldsymbol{z}'_{ib}\boldsymbol{\theta} + \varepsilon_{ib}, \tag{2}$$

where $\boldsymbol{z}_{ij}$, $j = a,b$, includes characteristics specific to the patient as well as to the choices. Let $\boldsymbol{z}_{ij} = [\boldsymbol{x}_{ij}, \boldsymbol{w}_i]$ and $\boldsymbol{\theta} = [\boldsymbol{\beta}', \boldsymbol{\alpha}']$. The vector $\boldsymbol{x}_{ij}$ denotes the attributes of the hospitals and, thus, varies across choices and possibly across patients as well. $\boldsymbol{w}_i$ contains the characteristics of the patient and is, therefore, the same for the two hospitals. Finally, ε_{ia} and ε_{ib} represent the stochastic elements that are specific to patients and hospital and known only by the individual.[6]

Following Martínez-García *et al.* (1998), $\boldsymbol{w}_i$ comprises variables like gender, age, whether or not the patient is exempt from copayments, and the severity of the patient's condition (health status). The vector $\boldsymbol{x}_{ij}$ includes, for example,

[6] This model is a version of a model presented by Green (2000), chapter 18.

the traveling time patients face to go to the hospital, the waiting time at the hospital, and its capacity. Travelling and waiting times are the non-monetary cost patients must incur when seeking care. Hence, it is expected that longer waiting times and a more distant location are associated with a lower probability of utilization of a given hospital.

Aiming at examining the effect of hospital-specific attributes—namely, traveling and waiting times—, the conditional logit model is adopted. Its link with utility maximization is as follows. Let $y_i = a$ represent patient i's choice of hospital a and $y_i = b$ patient i's choice of hospital b. Observing $y_i = a$ implies that patient i retrieves greater utility from option a. That is, $U_{ia} > U_{ib}$. With ε_{ij}independentely and identically distributed according to the type 1 extreme value distribution, the probability that each hospital is chosen is given by:

$$Prob(y_i = a) = Prob(U_{ia} > U_{ib}) = \frac{\exp(\boldsymbol{x}'_{ia}\boldsymbol{\beta} + \boldsymbol{w}'_i\alpha)}{\sum_{j=a}^{b} \exp(\boldsymbol{x}'_{ij}\boldsymbol{\beta} + \boldsymbol{w}'_i\alpha)}, \quad (3)$$

and

$$Prob(y_i = b) = Prob(U_{ib} > U_{ia}) = \frac{\exp(\boldsymbol{x}'_{ib}\boldsymbol{\beta} + \boldsymbol{w}'_i\alpha)}{\sum_{j=a}^{b} \exp(\boldsymbol{x}'_{ij}\boldsymbol{\beta} + \boldsymbol{w}'_i\alpha)}. \quad (4)$$

As Green (2012) notes, the terms that are specific to the patient fall out of the probability, which is expected in a model that compares the utilities of the alternatives. Equation (3) and (4) then simplify to:

$$Prob(y_i = a) = \frac{\exp(\boldsymbol{x}'_{ia}\boldsymbol{\beta})}{\sum_{j=a}^{b} \exp(\boldsymbol{x}'_{ij}\boldsymbol{\beta})}, \quad (5)$$

and

$$Prob(y_i = b) = \frac{\exp(\boldsymbol{x}'_{ib}\boldsymbol{\beta})}{\sum_{j=a}^{b} \exp(\boldsymbol{x}'_{ij}\boldsymbol{\beta})}. \quad (6)$$

Following Sivey (2012), an outside option, which could represent the choice to go private or forgo treatment, is not included in the model. It is assumed that U_{ij} is sufficiently high enough at one of the hospitals for the patient to always seek treatment, which implies a fixed overall demand for treatment, with the model coefficients determining the choice between the two hospitals. As in Sivey (2012), this may be interpreted as a model for the second stage in a two-stage decision process, where the patient firstly decides whether or not to seek treatment and secondly which hospital to seek treatment from.

4. Econometric Procedure

In order to estimate $\boldsymbol{\beta}$, I follow the maximum likelihood approach. The choice between hospitals a and b of each of n patients is treated as a single draw from a Bernoulli distribution. Given the data for the n independent observations, the joint probability function, or likelihood function, is given by:

$$Prob(Y_1 = y_1, \dots, Y_n = y_n|\boldsymbol{x}) = L(\boldsymbol{\beta}|\boldsymbol{x}) = \prod_{i=1}^{n} \prod_{j=a}^{b} [Prob(y_i = j)]^{d_{ij}}, \tag{7}$$

where d_{ij} is an indicator equal to one if hospital j is chosen by patient i.

Therefore, the log of choice probabilities over hospitals and patients takes the form of the log-likelihood:

$$Ln\ L(\boldsymbol{\beta}|\boldsymbol{x}) = \sum_{i=1}^{n} \sum_{j=a}^{b} d_{ij} ln \left[\frac{\exp(\boldsymbol{x}'_{ij}\boldsymbol{\beta})}{\sum_{k=a}^{b} \exp(\boldsymbol{x}'_{ik}\boldsymbol{\beta})} \right] \tag{8}$$

The maximum-likelihood estimator of $\boldsymbol{\beta}$, $\widehat{\boldsymbol{\beta}}$, is such that:

$$\widehat{\boldsymbol{\beta}} = \underset{\boldsymbol{\beta}}{\operatorname{argmax}}\ ln\ L(\boldsymbol{\beta}|\boldsymbol{x}) \tag{9}$$

5. Portuguese National Health System

The Portuguese National Health System (SNS) is universal, comprehensive and almost free at the point of use. In addition to it, citizens may benefit from additional insurance coverage in the form of public health subsystems, private health subsystems, and voluntary health insurance.

The SNS is predominantly financed through taxation, although out-of-pocket expenditures exist in the form of copayments, which are charged for services ranging from consultation to emergency visits and differ with the level of care.[7] They are defined as a fixed amount charged for a service, and their core objective is to regulate demand for public services. Copayments in the SNS correspond only to a small share of the total cost of service. For instance, in 2015 the copayment in polyvalent emergency services was €20.60 but the total cost was estimated to be €112.07, roughly 8.4%.[8] In the SNS as a whole, as of 2012, copayments amounted to approximately 1.69% of total NHS revenue, according to the Portuguese Health Regulator (Entidade Reguladora da Saúde – ERS).[9] Furthermore, 6.136.188 citizens, 59% of the population, are exempt from copayments.[10]

In the Portuguese Emergency Network, emergency services are classified according to the complexity of the cases they are qualified to treated and the availability of resources as polyvalent, medical-surgical and basic.[11] The polyvalent emergency services are endowed with a greater number of medical specialties and equipped with more resources, corresponding to the

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[7] Decreto-lei n.º 117/2014 (2014.Ago.05). DIÁRIO DA REPÚBLICA: I SÉRIE. n.º 149 pp. 4065-4069

[8] Circular Normativa da ACSS N.º1/2015/DPS/ACSS and Portaria n.º 234/2015 (2015.Ago.07) DIÁRIO DA REPÚBLICA: I SÉRIE. n.º 153 pp. 5516-5654

[9] *O Novo Regime Jurídico das Taxas Moderadoras*, Entidade Reguladora da Saúde, available at https://www.ers.pt/uploads/writer_file/document/892/Estudo_Taxas_Moderadoras.pdf (2016/05/11; 15H44M)

[10] Administração Central do Sistema de Saúde, IP. 2016. Taxas moderadoras. Available at http://www.acss.min-saude.pt/Publicações/TabelaseImpressos/TaxasModeradoras/tabid/142/language/pt-PT/Default.aspx (2016/08/13; 15H05M)

[11] Despacho n.º 10319/2014 (2014.Ago.11) DIÁRIO DA REPÚBLICA: II SÉRIE. n.º 153 pp. 20673-20678

more differentiated level of response to situations of emergency. Medical-surgical emergency services are at an intermediate level, referring to the polyvalent emergency services patients that require more specialized care. Basic emergency services treat only patients with milder conditions, directing the more severe cases to further differentiated hospitals in their referral network.

In Portuguese hospitals, emergency services are obliged to announce in the entrance the number of patients and a measure of the waiting time between triage and the first medical examination for each Manchester Triage System (MTS) classification. The methodology adopted to estimate the waiting time is the arithmetic mean of all emergency care episodes that took place in the previous two hours until the moment of update. The estimate is updated every five minutes.[12]

[12] For further information see http://tempos.min-saude.pt/#/info (2016/11/06;15H49)

6. Empirical Application

6.1 Data and Descriptive Statistics

The data was retrieved from the ALERT® database of the polyvalent emergency services of two public Portuguese hospitals located in the city of Porto. The original dataset was comprised of 23,680 observations, referring to all the patients aged 18 and over who sought emergency care at either hospital during the month of April 2016. For each observation, information regarding the hospital from which emergency care was demanded, the date, the patient's age, gender, copayment exemption status, classification of the MTS—color of the bracelet—, and parish of residence, the time between admission and triage, and the time between triage and the first medical examination was obtained.[13]

Following the discussion of the previous section and in order to ensure that only patients who actually chose to seek treatment from one of the two alternatives were included in the sample, only patient initiated contacts are considered. This implies that patients who had been referred from other providers were excluded from the sample, as well as those who had been transported by ambulance. Patients living outside the Porto district were also removed to control for situations in which emergency treatment was demanded by patients that would not normally chose any of the hospitals due to their residence—this includes, for example, the case of individuals visiting the region at the time of demand. Finally, observations for which there were missing values for any of the variables were excluded, as well as those for which waiting times displayed negative values, probably due to errors in the introduction of the data.

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[13] Grupo Português de Triagem. 2016. Sistema de Triagem de Manchester. Available at http://www.grupoportuguestriagem.pt/index.php?option=com_content&view=article&id=4&Itemid=110 (2016/08/13; 14H57M)

After these changes, the sample was reduced to 16,380 observations. Table 1 presents descriptive statistics for the original data retrieved from the hospitals. Traveling times to each hospital, computed using the information regarding the patients' address, is also reported.

	Mean	S.D.	Min.	p25	p50	p75	Max.
y_i=a	0.579	0.494	0.000	0.000	1.000	1.000	1.000
Age	53.289	19.833	18.000	37.000	53.000	69.000	108.000
Female	0.540	0.498	0.000	0.000	1.000	1.000	1.000
Exempt	0.525	0.499	0.000	0.000	1.000	1.000	1.000
Blue	0.016	0.127	0.000	0.000	0.000	0.000	1.000
Green	0.228	0.419	0.000	0.000	0.000	0.000	1.000
Yellow	0.640	0.480	0.000	0.000	1.000	1.000	1.000
Orange	0.112	0.315	0.000	0.000	0.000	0.000	1.000
Red	0.004	0.063	0.000	0.000	0.000	0.000	1.000
Traveling time	16.566	8.221	3.000	12.000	15.000	20.000	87.000
Time Admission/ Triage	8.330	7.947	0.400	3.300	6.333	11.067	250.500
Time Triage/ Examination	75.906	92.937	0.150	15.100	36.508	103.242	859.333

Table 1 Descriptive Statistics for the original data retrieved from the hospitals (16,380 observations).

Note: y_i = a if chosen hospital is hospital a, y_i = b if chosen hospital is hospital b; age = number of years of age; female = 1 if female, female = 0 if male; exempt = 1 if exempt from copayments, exempt = 0 if non-exempt from copayments. Blue, Green, Yellow, Orange, and Red are dummy variables = 1 for patients with the according color of bracelet in the MTS classification.

The median patient is a 53-year-old woman, who is not exempt from copayments. She seeks emergency care from hospital *a*, where she is classified as a yellow case in the MTS. Besides facing a 15-minute traveling time, she waits approximately 6 minutes between admission and triage, and another 36.5 minutes until the first medical observation.

In order to estimate the conditional logit model, as discussed in section 3, the original data was used to derive hospital-specific attributes.

Traveling times are the shortest period of time, measured in minutes, required to travel from the patient's parish to each hospital. [14]

In the spirit of Sivey (2012), although available, actual waiting times for each patient at the hospital they visited are not used. The conditional logit model requires the inclusion of waiting times for each hospital in the choice set, and the waiting time patients may have waited had they chosen the other hospital is unknown. Thus, two measures of waiting times for each hospital were constructed instead.

For the waiting time between admission and triage, the measure of waiting time for each patient is the daily median waiting time between admission and triage, in the day they demanded emergency care, at each hospital. It is assumed that, at the arrival at the hospital site, patients form an expectation of the waiting time between admission and triage by assessing the number of people in the queue. The daily median is used as oppose to the mean to offset the impact of outliers.

For the waiting time between triage and the first medical observation, the measure of waiting time for each patient is the daily median waiting time between triage and the first medical observation for the MTS classification they received, in the day they demanded emergency care, at each hospital. The underlying assumption here is that patients would have received the same MTS classification in the two hospitals. The choice of this measure is justified on additional grounds.

[14] The time needed to travel from the patient's residence to the hospital was computed using the software Google Maps™.

Firstly, in the entrance of emergency rooms, Portuguese hospitals are obliged to announce a measure of the waiting time between triage and first medical examination for each MTS classification. Therefore—since this information is available to patients at the moment of the choice between staying at the hospital they arrived or seeking care from another hospital—it plausible to assume that it is factored in the decision process. Further, it is the expectation of the waiting time and not its *ex-post* realization that matters for the utility comparison at the moment of choice.

Secondly, following Sivey (2012), the median is used in opposed to the mean to reduce the effect of outliers—which may be inferred from Table 1. According to the discussion of the previous section, each emergency care episode is included in the mean computed and made available to patients at the hospitals only for two hours. This implies that the effect of extreme values of waiting times have a short-lived effect on that measure. Since the dataset only allows to compute daily averages of waiting times, the effect of outliers would be larger in that average than it is in the set of averages available to patients. As such, it is argued that the daily median is a more accurate proxy for the information patients take into account in the moment of choice.

Finally, for a few patients, mainly classified as blue and red cases, the measure of waiting time could not be computed due to the inexistence of patients with the same MTS classification in the not chosen hospital in the same day. Consequently, the estimation sample was reduced to 16,310 cases (patients) and 32,620 observations.

Table 2 summarizes the independent variables used in the conditional logit estimation.

Variables	Description
traveling	Shortest period of time, measured in minutes, required to travel from the patient's parish to each hospital.
medianwaiting1	Daily median waiting time between admission and triage for each hospital.
medianwaiting2	Daily median waiting time between triage and the first medical observation for each MTS classification at each hospital.
epblue	Daily number of patients classified as *non-urgent* in the MTS classification (blue bracelet) at each hospital.
epgreen	Daily number of patients classified as *standard* in the MTS classification (green bracelet) at each hospital.
epyellow	Daily number of patients classified as *urgent* in the MTS classification (yellow bracelet) at each hospital.
eporange	Daily number of patients classified as *very urgent* in the MTS classification (orange bracelet) at each hospital.
epred	Daily number of patients classified as *immediate* in the MTS classification (red bracelet) at each hospital.

Table 2 Variable description.

Table 3 reports descriptive statistics for the variables used in the estimation.

	Mean	S.D.	Min.	p25	p50	p75	Max.
d_{ij}	0.500	0.500	0.000	0.000	0.500	1.000	1.000
age	53.282	19.829	18.000	37.000	53.000	69.000	108.000
female	0.540	0.498	0.000	0.000	1.000	1.000	1.000
exempt	0.475	0.499	0.000	0.000	0.000	1.000	1.000
epblue	4.554	4.139	0.000	1.000	3.000	7.000	18.000

epgreen	62.934	31.533	17.000	34.000	58.000	90.000	123.000
epyellow	176.562	23.749	120.000	159.000	178.000	193.000	230.000
eporange	30.975	11.362	11.000	21.000	31.000	41.000	56.000
epred	1.101	1.104	0.000	0.000	1.000	2.000	4.000
traveling	18.262	8.516	3.000	13.000	17.000	23.000	87.000
medianwait1	6.599	1.862	2.767	5.167	6.350	7.333	11.183
medianwait2	45.223	29.757	0.150	29.517	39.600	53.050	417.700

Table 3 Descriptive Statistics for the estimation sample (32,620 observations).

The median patient is a 53-year-old woman, who is not exempt from copayments.[15] Among the two choices, the composition of emergency care demand, on the day the median patient seeks treatment, is as follows: 3 blue, 58 green, 178 yellow, 31 orange, and 1 red cases. Also among the two choices, the median patient faces a 17-minute traveling time, waits 6.35 minutes between admission and triage and almost 40 minutes until the first medical observation.

In order to estimate the model it is assumed that $\boldsymbol{x}_{ij}$ are exogenous to every decision-maker—*i.e.*, the patient. As Sivey (2012) notes, this is a plausible assumption given that the patients are relatively small and numerous compared to the hospitals, making the effect of the marginal patient on waiting times negligible. In fact, it seems unlikely that an individual patient choice of hospital would have an impact in a given hospital's waiting times. However, to control for possible effects of demand on waiting times, the number of daily episodes by MTS classification are included in $\boldsymbol{x}_{ij}$.

6.2 Preliminary Analysis

In this subsection, a first data-driven attempt to investigate the link between waiting times and the demand for emergency care is carried out. To the extent

[15] Note that statistic for patient-specific atributes are naturally unchanged from Table 1.

that there is one, the relationship between waiting times and demand might not be strictly demand-sided. If it is, as discussed in Sections 1 and 2, waiting times assume the role of a demand-curbing mechanism by acting like a non-monetary price. All else equal, it is expected that lower waiting times lead to increased demand. However, it may be the case that the relationship is supply-sided in the sense that waiting times are a result of excess demand. That is, waiting times increase because demand is above the hospital's capacity.

Table 4 presents descriptive statistics for the traveling and waiting times variables for the chosen and not chosen hospital. From the table, no consistent pattern between traveling time, waiting time, and choice can be inferred. On average, traveling time is shorter for the chosen hospital, waiting times between admission and triage are similar, and waiting times until the first medical observation are longer in the chosen hospital for except for high severity cases (orange and red). Considering the median instead yields identical conclusions. This implies that traveling time may be an important determinant of hospital choice, while waiting times may not. This type of analysis, however, has the significant shortcoming of considering each variable individually, which diminishes the validity of its conclusions.

Chosen hospital							
	Mean	S.D.	Min.	p25	p50	p75	Max.
traveling	16.570	8.220	3.000	12.000	15.000	20.000	87.000
medianwait1	6.608	1.887	2.767	5.167	6.350	7.333	11.183
medianwait2 (blue)	138.507	110.206	10.600	43.400	90.650	235.367	417.700
medianwait2 (green)	44.915	15.934	19.300	32.717	41.300	53.367	99.908

medianwait2 (yellow)	50.033	26.049	24.550	33.400	40.892	56.117	161.892
medianwait2 (orange)	15.734	8.761	4.350	8.850	12.650	20.400	41.767
medianwait2 (red)	16.156	10.771	0.150	8.708	14.350	21.433	39.450
Not chosen hospital							
traveling	19.954	8.472	3.000	14.000	18.000	25.000	87.000
medianwait1	6.589	1.837	2.767	5.167	6.350	7.333	11.183
medianwait2 (blue)	120.006	123.960	10.600	32.967	59.000	180.900	417.700
medianwait2 (green)	38.021	14.130	19.300	28.050	33.750	43.800	99.908
medianwait2 (yellow)	49.623	25.617	24.550	33.400	40.892	53.967	161.892
medianwait2 (orange)	18.269	8.257	4.350	12.317	19.000	23.500	41.767
medianwait2 (red)	17.796	11.996	0.150	10.200	16.267	23.350	39.450

Table 4 Descriptive Statistics for traveling and waiting time variables per choice.

7. Results and Discussion

Table 4 presents the results for three specifications of the conditional logit model.[16]

Specification 1 includes traveling and waiting times as sole explanatory variables. The estimates show a statistically significant negative effect of traveling and the waiting time between triage and the first medical observation on the probability of utilization and a statistically significant positive effect of *medianwait1*. In order to evaluate if these results are biased because of a correlation of waiting times and demand factors, a second specification that adds the daily number of episodes (patients) by MTS classification is estimated. The significance and the sign of the above results hold when the daily number of episodes by MTS classification—which are used to control for the possible correlation between waiting times and overall demand—are included. However, the absolute value of the coefficient of the traveling time variable increases, and the impact of waiting times is reduced in a non-trivial manner.

In order to evaluate whether these results are biased of correlation of waiting times with patient-specific characterizes a third specification is estimated. Specification 3 includes the traveling and waiting times variables, their interactions with patient-specific characteristics, and the daily number of episodes by MTS classification. The estimate for the effect of traveling time is robust across specifications and actually increases as more variables are included in the model. Although marginally, this effect is stronger for older patients and offset by copayment exemption, arguably because the total cost (monetary and non-monetary) is smaller for exempt patients. On the other hand, the sign of the coefficients on the waiting time variables are reversed in

[16] The model is estimated in STATA 13 using the *clogit* command.

the last specification. The effect of waiting time between admission and triage becomes insignificant, as well as that of its interactions. Besides the change in the sign of the effect of *medianwait2*, its magnitude is considerably small in all model specifications. The net effect of traveling and waiting times may be further investigated by analyzing the marginal effects reported in Table 5.

	Specification 1	Specification 2	Specification 3
traveling	-0.1271*** (0.0025)	-0.1562*** (0.0032)	-0.1947*** (0.0084)
× *age*			-0.0003*** (0.0001)
× *female*			0.0071 (0.0051)
× *exempt*			0.0945*** (0.0052)
medianwait1	0.0201*** (0.0069)	0.0144* (0.0081)	-0.0009 (0.0227)
× *age*			0.0002 (0.0004)
× *female*			-0.0076 (0.0142)
× *exempt*			0.0176 (0.0143)
medianwait2	-0.0045*** (0.0005)	-0.0018*** (0.0005)	0.0075*** (0.0016)
× *age*			-0.0001*** (0.0000)
× *female*			0.0004 (0.0010)
× *exempt*			-0.0096*** (0.0010)

epblue		-0.0051 (0.0043)	-0.0047 (0.0044)
epgreen		-0.0042*** (0.0007)	-0.0046*** (0.0008)
epyellow		0.0004 (0.0008)	0.0000 (0.0008)
eporange		-0.0067*** (0.0018)	-0.0073*** (0.0018)
epred		-0.0145 (0.0115)	-0.0176 (0.0117)
Obs.	32620	32620	32620
Cases	16310	16310	16310
Log L	-9688.6464	-9547.4357	-9244.0154

Table 5 Estimation Results.
Standard errors reported in parenthesis. *** p<0.01, **p<0.05, *p<0.1

The estimated marginal effects reveal that traveling time has a robust, statistically significant, negative effect on the probability of utilization, while confirming that the waiting time between admission and triage is not likely to affect demand decisions. As far as the impact of the waiting time between triage and the first medical observation is concerned, its net effect turns out to be negative, statistically significant, though very close to zero.

The estimates of Specification 3 imply that a standard deviation increase in the waiting time between triage and the first medical observation (approximately, 30 minutes) reduces the probability of seeking emergency care from a given hospital by 0.009 percentage points, *ceteris paribus*, which suggests that waiting times are a weak determinant of hospital choice. An increase of the same magnitude in the traveling time reduces the probability of utilization by 5.841 percentage points, *ceteris paribus*. Note that, due to the inclusion of the daily number of episodes, the marginal effect of *medianwait2* only captures the effect of supply-side induced changes in waiting times, such as changes in hospital capacity.

These results may be due to the nature of emergency care—*i.e.*, patients in urgent need of medical care are unlikely to forgo treatment even when faced with a high time cost—or to the fact that patients only learn the expectation of waiting times at the hospital site, and, once they arrive, traveling to another hospital might not be a suitable alternative to most patients. This is consistent with the larger effect of traveling times, which may be anticipated by patients at a prior point in time.

	Specification 1	Specification 2	Specification 3
traveling	-0.0294***	-0.0378***	-0.0394***
	(0.0005)	(0.0008)	(0.0008)
medianwait1	0.0047***	0.0035*	0.0031
	(0.0016)	(0.0020)	(0.0020)
medianwait2	-0.0010***	-0.0004***	-0.0003**
	(0.0001)	(0.0001)	(0.0001)
epblue		-0.0012	-0.0011
		(0.0010)	(0.0011)
epgreen		-0.0010***	-0.0011***
		(0.0002)	(0.0002)
epyellow		0.0001	0.0000
		(0.0002)	(0.0002)
eporange		-0.0016***	-0.0017***
		(0.0004)	(0.0004)
epred		-0.0035	-0.0042
		(0.0028)	(0.0028)

Table 6 Marginal Effects at the mean.

Standard errors reported in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Finally, the goodness of fit of Specification 3 is assessed by cross tabulating the predicted, $\hat{y}_i$, versus actual outcome, y_i, in Table 6. Predicted outcomes are defined as:

$$\hat{y}_i = a \; if \; \widehat{Prob(y_i = a)} > \widehat{Prob\,(y_i = b)}, \tag{10}$$

where $\widehat{Prob}(\cdot)$ denotes the estimated probability according to Specification 3. The values of Table 6 yield a percentage of correct classifications of 72.05%.

Choice	Predicted choice		Total
	$\hat{y}_i = a$	$\hat{y}_i = b$	
$y_i = a$	7,950	1,480	9,430
$y_i = b$	3,078	3,802	6,880
Total	11,028	5,282	16,310

Table 7 Hit and Miss Analysis.

8. Policy Implications

From a policy standpoint, traveling times have limited relevance. Unless when deciding the site of construction of new health care facilities—which is usually a decision for the very long run that does not happen often—, policymakers cannot easily influence traveling times.

According to the results of the previous section, it is the waiting time between triage and the first medical observation that matter for patients' choice. Unlike traveling time, waiting times at the hospital site can be subject to policy intervention. By expanding medical capacity or increasing efficiency, waiting times between triage and the first medical observation might be reduced. If the results suggest that such policies would not foster consumer welfare a great deal, they also indicate that waiting times are not a suitable demand-curbing mechanism, contradicting the literature that assigns them a policy role.

Although the data does not allow for the estimation of consumer surplus, it is plausible to admit that changes in waiting times would not have significant impact on consumer welfare in the case of emergency care. It may be the case that patients are more tolerant to waiting once they arrive at the hospital site-—possibly, due to a safety feeling—or because going to a different hospital is not a suitable option for patients in need of emergency care. One way to make demand more responsive to waiting times is to make information regarding them available to consumers prior to their arrival at the hospital. The Portuguese ministry of health has already implemented policies towards that goal by making available online the same information on waiting times emergency services display at the site.

Finally, it is important to stress that if data from hospitals with different copayments is included, the framework may be used to evaluate the costs imposed on patients by traveling and waiting times, thereby complementing cost-benefit analysis of hospital location and emergency care management.

9. Concluding Remarks

In this study, patient choice of emergency care providers in a duopoly setting without outside option was analyzed. Placing emphasis on the role of hospital-specific attributes—traveling and waiting times—, a conditional logit model was estimated with data from two Portuguese public hospitals. The available dataset opened the possibility of dividing waiting times into two components: the period between admission and triage and the period between triage and the first medical observation. The major conceptual challenge, as is common in this type of works, was how to proxy the information available to patients regarding waiting times at the moment of choice.

Negative and statistically significant effects of traveling time and the time between triage and the first medical observation were found, even when controlling for patient-specific characteristics and for correlation between waiting times and aggregate hospital demand. The size of the effects, though, is quantitatively small, particularly for the measure of waiting time. The fact that traveling time seems to matter more than waiting time indicates that the former may not be—at least, entirely—factored in by patients at the moment of choice, arguably due to lack of information. In turn, this suggests that actual choice of emergency care provider might not occur at the hospital site, after collecting information that allows patients to form an expectation of the waiting time, but before arrival, when only traveling times are anticipated.

The low responsiveness of the probability of utilization of a given hospital to waiting times has somewhat striking policy implications. Both policymakers aiming at reducing waiting times in order to foster welfare or, conversely, policymakers wishing to use waiting times—as has been long proposed in the Health Economics literature—to discourage utilization may fall short of the intended goals.

It is noteworthy that such results might be motivated by the nature of emergency care itself and that they should not be carried over to other dimensions of health care provision lightly. Requiring immediate care, patients are likely to forgo search and seek treatment from the nearest provider or from the provider with which they have a previous or on-going relationship.

Finally, the major shortcomings of the current work are closely related to opportunities for further research. The most promising extension would be to collect data that allows for the possibility of including a measure of patients' opportunity cost. A common measure would be the hourly salary for employed patients. As the burden of waiting is closely related to what is sacrificed, controlling for the opportunity cost might provide additional and important insight into patient choice.

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