Econometric evaluation of waiting times for scheduled surgery in the Portuguese NHS

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Abstract

This thesis contains three essays that address the general topic of waiting times for scheduled surgery in the Portuguese National Health Service.

In the first essay, we analyse the gender gap (i.e. gross and adjusted gender gap) in waiting times for scheduled surgery, using about 2,6 million of observations concerning all surgical episodes that occurred in Portuguese national hospitals between 2011 and 2015. Without any control variables, we find a 10% gross differential between the waiting times of men and women, meaning that men wait on average 10% less than women. We then add several explanatory variables that can account for this difference. The variables are added in a way that permits the most flexible parametric specification. Nevertheless, our results still indicate that a waiting time differential of 3% persists, which cannot be accounted by the added covariates. Next, we use Gelbach's decomposition to understand the contribution of each variable to the observed reduction in the gender gap and confirm that patient priority and hospital fixed effects are the variables that contribute the most to the explained component of the gap. The analysis suggests that men tend to be ranked with more severe priorities and that there are hospital specificities that cause men to have shorter waiting times. Overall, our results exhibit a pattern where women have longer waiting times for surgeries, even when all obvious factors such as individual and hospital characteristics are accounted for. This work contributes to the literature on gender discrimination in scheduled surgery by examining all complete episodes that occurred in Portuguese hospitals. Because this study uses an alternative methodology it provides a more informative analysis as to the sources of the gender gap.

In the second essay, we studied equity as well as the impact of prioritisation in access to surgery. Thus, since we are now concerned with access to surgery, we analyse

surgical episodes along with cancellation episodes. The coverage of the database is identical to that in the first paper but given that it includes cancellations the total number of observations is larger, at around three million. Our objective now is the study of the waiting time for surgery in a framework that accounts for cancellations. Thus, we estimated duration models where cancellations are introduced as censored observations. In line with the first essay, the results show that men have shorter waiting times. Patients reported with cancer are also shown to have shorter waiting times, as well as patients with more severe priorities. Regarding the variable age, we found that patients aged 30 to 45 years have the lowest waiting times. If we exclude cancellations from the analysis the results turn out different. This suggests that studies of access to surgery in public hospitals as measured by waiting time should take cancellations into account. Finally, since we have available information on different motives for cancellation we tried to understand if there are particular factors affecting the reasons for cancellation. Thus, we estimated a multinomial logit model using all cancellation episodes. As a result, we identified the patient groups that were most exposed to specific cancellations. Additionally, we concluded that the priority noncompliance also plays a relevant role in explaining the type of cancellation.

In the third essay, we analysed the spatial interactions between Portuguese NHS hospitals using data for the period of 2013-2015. Based on patient-level data we estimated two hospital-specific indexes to capture the surgery waiting times and the probability of cancellation for each hospital. Because of the way the indexes are created they are purged of demand-side characteristics and should reflect only aspects related to the management and organisation of the hospitals as well as factors originating on the supply-side. We next estimated spatial panel models using the hospital indexes as dependent variables and taking into account variables related to the hospital's organisational structure, its size, and the fact that the hospital has medical teaching or not. The results are apparently robust showing evidence of spatial dependence on both indexes. Thus, it seems that there are spillovers effects on waiting lists that could be used to optimise the access to scheduled surgery, namely, entering into agreements with the social sector to increase surgery supply.

Resumo

Esta tese contém três ensaios que abordam o tópico geral de tempos de espera para cirurgia programada no Serviço Nacional de Saúde Português. No primeiro ensaio, analisamos a diferença de género (ou seja, diferença bruta e ajustada) nos tempos de espera para a cirurgia programada, usando cerca de 2,6 milhões de observações sobre todos os episódios cirúrgicos que ocorreram nos hospitais nacionais portugueses entre 2011 e 2015. Sem nenhuma variável de controlo, encontramos um diferencial bruto de 10 % entre os tempos de espera de homens e mulheres, o que significa que os homens esperam em média 10 % menos que as mulheres. Em seguida, adicionamos diferentes variáveis explicativas que podem justificar essa diferença. As variáveis são adicionadas de maneira a permitir uma especificação paramétrica mais flexível. No entanto, os nossos resultados ainda indicam que um diferencial de tempo de espera de 3 % persiste, o que não pode ser contabilizado pelas covariáveis adicionadas. Em seguida, usamos a decomposição de Gelbach para entender a contribuição de cada variável para a redução observada na diferença de género e confirmar que a prioridade do paciente e os efeitos fixos hospitalares são as variáveis que mais contribuem para o componente explicada da diferença. A análise sugere que os homens tendem a ser classificados com prioridades mais severas e que existem especificidades hospitalares que fazem com que os homens tenham tempos de espera mais curtos. No geral, os nossos resultados exibem um padrão em que as mulheres têm mais tempo de espera para cirurgias, mesmo quando todos os fatores óbvios, como caraterísticas individuais e hospitalares, são contabilizados. Este trabalho contribui para a literatura sobre discriminação de género em cirurgia programada, examinando todos os episódios completos que ocorreram em hospitais portugueses. Como este estudo utiliza uma metodologia alternativa, fornece uma análise mais informativa sobre as fontes da diferença de género.

No segundo ensaio, estudamos a equidade e o impacto da priorização no acesso a cirurgia. Assim, como agora estamos preocupados com o acesso a cirurgia, analisamos os episódios cirúrgicos juntamente com os episódios de cancelamento. A cobertura da base de dados é idêntica à do primeiro artigo, mas como inclui cancelamentos, o número total de observações é maior, em torno de três milhões. O nosso objetivo agora é o estudo do tempo de espera pela cirurgia em uma estrutura que justifique os cancelamentos. Assim, estimamos modelos de duração em que os cancelamentos são introduzidos como observações censuradas. Em linha com o primeiro ensaio, os resultados mostram que os homens têm tempos de espera mais curtos. Os pacientes reportados com cancro também apresentam tempos de espera mais curtos, assim como os pacientes com prioridades mais severas. Em relação à variável idade, constatamos que os pacientes entre 30 a 45 anos apresentam os menores tempos de espera. Se excluirmos os cancelamentos da análise, os resultados serão diferentes. Isso sugere que os estudos de acesso à cirurgia em hospitais públicos, medidos pelo tempo de espera, devem levar em consideração os cancelamentos. Finalmente, como temos informação disponível sobre os diferentes motivos para cancelamento, tentamos entender se existem fatores específicos que afetam os motivos do cancelamento. Assim, estimamos um modelo de logit multinomial usando todos os episódios de cancelamento. Como resultado, identificamos os grupos de pacientes que foram mais expostos a cancelamentos específicos. Concluímos que o não cumprimento da prioridade também desempenha um papel relevante na explicação do tipo de cancelamento.

No terceiro ensaio, analisamos as interações espaciais entre os hospitais portugueses do SNS usando dados para o período de 2013-2015. Com base nos dados ao nível do paciente, estimamos dois índices específicos ao hospital para capturar os tempos de espera da cirurgia e a probabilidade de cancelamento de cada hospital. Devido à forma como os índices são criados, eles estão expurgados das características do lado da procura e devem refletir apenas aspetos relacionados com a gestão e organização dos hospitais, bem como fatores originados no lado da oferta. Em seguida, estimamos modelos de dados em painel usando os índices hospitalares como variáveis dependentes e levando em consideração variáveis relacionadas com a estrutura organizacional do hospital, tamanho e o facto de o hospital ter ensino de medicina. Os resultados são aparentemente robustos, mostrando evidência de dependência espacial em ambos os índices. Assim, parecem existir efeitos de spillover nas listas de espera que podem ser usados para otimizar o acesso a cirurgia programada, nomeadamente com a celebração de acordos com o setor social para aumentar a oferta de cirurgia.

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Introduction

Waiting times for scheduled treatment are a persistent problem in countries with national health services, which are mostly tax-funded and characterised by reduced copayments. The pressures on public budgets due to the rising of health expenditures, driven by factors such as population ageing, technological innovation costs or higher population expectations (Marino et al., 2017), lead to managing access to surgery mechanisms. Since demand for scheduled surgery is higher than supply, increasing waiting times is then seen as a rationing mechanism and it is often a topic of political discussion and research interest (Siciliani et al., 2013).

With this topic in mind, the “OECD Project on Waiting Times” in 2001, and the “Second OECD Waiting Time Project” between 2011-2012, were carried out to investigate and compare excessive waiting times for non-emergency surgery in some countries, producing several research papers (e.g., Siciliani and Hurst, 2003, 2005; Siciliani et al., 2014). In addition to recognising that longer waiting times are a source of patient dissatisfaction that may negatively impact the public perception of health systems quality, a deterioration of patients’ health status cannot be denied.

A number of initiatives have been introduced in several countries to face the waiting lists and Portugal was not an exception (Siciliani et al., 2014). In June 2004, the Portuguese government created the Integrated Management System of the Waiting List for Surgery - “Sistema Integrado de Gestão de Inscritos para Cirurgia” (SIGIC) to regulate all scheduled surgical activity (Barros et al., 2013). In addition to seeking to reduce waiting times for surgery, SIGIC also aims at providing an equitable access to surgery and more efficient resources’ management as well.

In the years following its creation the contribution of SIGIC to the waiting times reduction was well noticed (Siciliani et al., 2014). However, the latest economic crisis has brought challenges by budgetary constraints for the various European health systems, namely, for the Portuguese NHS (OECD/EU, 2016).

Thus, in line with the latest research, our study seek to contribute to a better understanding of waiting times for scheduled surgery using the Portuguese NHS as a case study. In our view, this thesis is able to provide some clues which may help to establish guidelines to control waiting times and ensure better equity in access to surgery. Furthermore, we also give a contribution to the literature on surgery waiting times by showing how different econometric methods may be harnessed to answer relevant questions on this literature.

In the first chapter, we contributed to the literature on gender discrimination in scheduled surgery, using all surgery episodes performed in Portuguese hospitals between 2011 and 2015. Literature on surgery waiting times is still very focused on using gender as a control variable rather than analysing the factors that impact on waiting times by gender. In our understanding, our methodology guarantees a more informative analysis on the sources of gender difference.

In the second chapter, our research question lies in the analysis of surgery access, in terms of equity and prioritisation. In comparison with the first chapter, in which we use only the surgery episodes, we introduce cancellations along with the surgery episodes to provide a full picture of surgery access. In addition to identifying patients' characteristics that influence waiting times, we are also able to identify the patients' groups most exposed to cancellations and the role of the patient's priority and priority noncompliance as well.

In the third chapter, our research topic focuses on the surgery supply-side. Our study allows us to identify the hospital's features, for instance, related to management and organisation models that may be relevant to explain surgery waiting times and the probability of cancellation, and therefore, contribute to improving access to surgery. Here, we use spatial econometric models to account for the existence of possible spillover effects.

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Chapter 1

Explaining the gender gap in waiting times for scheduled surgery in the Portuguese NHS

Abstract

This study evaluates whether there is a gender gap in waiting times for scheduled surgery in the Portuguese National Health Service between 2011 and 2015. We start with a gross gap in which men have 10% shorter waiting times. We then estimate a regression model on waiting times that controls for multiple sources of heterogeneity. The results still indicate an unexplained differential where men have 3.1% shorter waiting times than women. Employing the Gelbach's decomposition, we find that patient's priority is the variable that contributes the most to the explained gap followed by hospital fixed-effects. The results show that decision-makers should pay more attention to a pattern that seems to disadvantage women. Overall, we consider that our approach provides a more informative assessment of the sources of the gender gap on waiting times to health than previous literature.

Keywords: waiting times, scheduled surgery, gender gap, high-dimensional fixed effects, Gelbach's decomposition, Portugal

JEL Classification: *I14*, *C01*

1.1 Introduction

Equity in access is a central theme in universal health care systems (Johar et al., 2013), in that the severity of the patient's clinical condition should be the only relevant factor in explaining waiting times. However, there is a set of variables besides severity that impact on access (e.g.: gender, age, income) (Cooper et al., 2009; Landi et al., 2018; Laudicella et al., 2012).

In recent decades, the term gender gap or gender bias has gained relevance in health research (Łyszczarz, 2017) and has been widely discussed in the literature on health in diverse topics such as the mortality, morbidity and healthcare utilisation (Alspach, 2012; Arber, 1997; Bertakis et al., 2000; McDonough and Walters, 2001; Read and Gorman, 2010).

Although gender bias corresponds to an unequal treatment of individuals based on their gender, Alspach (2012) noticed the gender gap in health care literature predominantly refers to when "female patients are assessed, diagnosed, referred, and treated not only differently but at a lower level of quality" which may cause worsening of women's health status.

Underestimating or misunderstanding women's health condition, differences in the way men and women perceive and experience their illness, unconscious prejudice or explicit discrimination are some of the reasons for the gender gap (Alspach, 2012; Łyszczarz, 2017).

Understanding the factors that condition access to healthcare by gender is an important contribution to the literature and health policy (Payne, 2009) since it allows to improve healthcare provided to men and women, as well as their health outcomes, and increase efficiency by optimizing hospital resources (Kuhlmann and Annandale, 2015). However, the gender gap still receives little attention from health decision makers (Kuhlmann and Annandale, 2010).

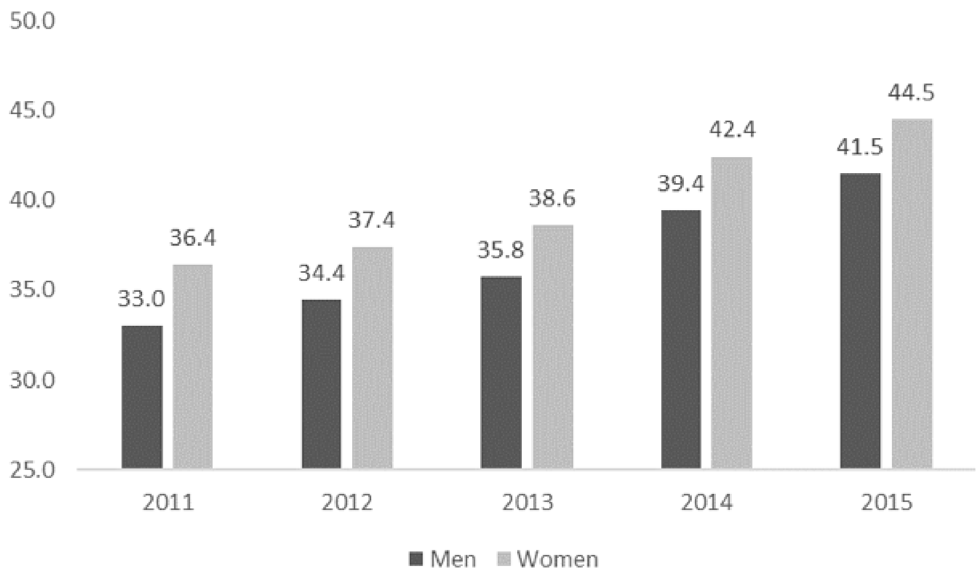
Thus, our study contributes to healthcare discussion at analysing the waiting times for scheduled surgery, a feature usually associated with national health systems - those mainly financed by taxes and with reduced co-payments (Gutacker et al., 2016; Kaarboe and Carlsen, 2014), focusing on the study of the differential of waiting times between men and women.

Since all individuals have the right to access and be treated in the National Health Service (NHS), there is an excess demand that translates into longer waiting times and waiting lists. In Portugal, waiting lists and waiting times have been over the years an important health policy topic (Barros et al., 2013) leading to the creation of the Integrated Management System for the Surgery Waiting List "Sistema Integrado de Gestão de Inscritos para Cirurgia" (SIGIC) in 2004.

The SIGIC main goals were: 1) to reduce waiting times; 2) to ensure the equity of access; 3) to promote the overall efficiency of the system and; 4) to provide information quality and transparency (Gomes and Lapão, 2011).

In the years after the SIGIC creation, there was a decrease in waiting times (Barros et al., 2013), but in recent years we have witnessed a trend reversal. In fact, it is clear that average waiting times for the operated patients have been increasing in recent years (ACSS, 2017), as can also be seen in Figure 1.1.

Figure 1.1: Median waiting times (days) of operated patients between 2011 and 2015



Two valuable insights can be retained from Figure 1.1: waiting times have been increasing; women wait longer than men for scheduled surgery. It is, thus, suggested that there is a gap in waiting times between men and women. However, we must control for a set of confounding variables to understand the source of this observed differential before we can establish whether SIGIC programme guarantees gender "equity of access".

Our study uses more than 2.6 million observations (at patient-level) from the Portuguese NHS between 2011 and 2015 and estimates a regression model with multiple fixed effects to control for observed and unobserved heterogeneity. Some of these fixed effects are high-dimensional and it would not be possible to implement the estimation with conventional methods.

In fact, this is one of the contributions of this paper to the literature, since we show that accounting for multiple sources of heterogeneity reduces the bias of the unadjusted estimate for the gender gap. Furthermore, using Gelbach's decomposition we estimate the relative contribution of each variable to the explained component of the observed gender gap. This is an additional contribution of our work, which allows to investigate whether there are indications of discriminatory motivations or clinical reasons that partially explain the gender differential. To our knowledge, there are no previous studies on waiting times to healthcare that use these methodologies.

The rest of this paper is organised as follows. In section 2 we provide a brief review of the relevant literature. Section 3 describes the methodology used in this paper. Our results are presented in section 4 and discussed in section 5. Section 6 concludes.

1.2 Literature review

Even though it is usually accepted that "waiting times should only depend on the need or severity of the patient" (Laudicella et al., 2012), there is a large literature identifying inequalities in waiting times. The majority of these studies focus less on the gender gap than on the socioeconomic status (Abásolo et al., 2014; Cooper et al., 2009; Johar et al., 2013; Kaarboe and Carlsen, 2014; Laudicella et al., 2012; Moscelli et al., 2018; Smirthwaite et al., 2016).

Table 1.1 identifies the contributions of the most relevant literature in waiting lists for scheduled treatment.

Table 1.1: Studies of inequalities in waiting times

Authors	Sample	Model specification	Independent or control variables	Main findings about gender
Moscelli et al. (2018)	Elective patients for CABG[a] surgery or PCI[b] from the financial year 2002/03 to 2010/11 in NHS-funded hospital admissions in England (n=321,076) – Administrative data	Log-normal models to explain waiting times for each CABG surgery and PCI, by financial year	Gender, age, income deprivation, number of diagnoses, past emergency utilisation, hospital-fixed effects, Charlson comorbidities, admission month	In general, women wait significantly longer than men in both surgeries (not adjusted for self-selection)
Landi et al. (2018)	Health visits in the Italian NHS service in 2013 (n=48,473) – Survey data	Multivariate logistic regression models for three services: specialist visits, diagnostic, an elective surgery; to explain excessive waiting times	Gender, age, economic resources, education level, marital status, self-perceived health, health limitations, household overcrowding, chronic diseases	There were significant differences across gender in specialist visits, where women were most likely to have excessive waiting times.
Smirthwaite et al. (2016)	Data on cataract extraction in Sweden from 2010 to 2011 (n=102,532 patients) – Administrative data	Linear regression models to explain waiting times	Gender, age, annual income, education level, native country, month, hospital and a variable that measures whether the patient was working or was retired	Women had longer waiting times in cataract extraction. Nevertheless, the authors also noted the differences were very small and even in the case of statistically significance, they were not clinically relevant
Abásolo et al. (2014)	Medical specialist consultations from Spanish NHS in 2006 (n=2,462 observations) – Survey data	Log-normal and Gamma models to explain waiting times for diagnosis visits and review visits	Gender, age, income and educational levels, self-reported measures of patient's health state, employed status, whether the patient is resident in a rural area, double health insurance, if the household have members who need special care	Women had significant 13.6% longer waiting times for diagnosis visits compared to men
Kaarboe and Carlsen (2014)	Elective inpatient/outpatient treatment in somatic hospitals in Norway, 2004-2005 (n= 611,414 records) – Administrative data	Log-normal specification for each group (men and women separately) to explain waiting times	Age, income, education level, main and secondary diagnoses, surgical procedures, hospital supply, choice variables, travelling time	It was shown that women had higher waiting times than men in the 3 groups of hospitals (local hospitals, university hospitals and other hospitals)
Johar et al. (2013)	Non-emergency surgical treatment from 2004 to 2005 for public hospitals in the state of New South Wales (Australia) (n=90,162) – Administrative data	Log-normal models with waiting times as dependent variable	Gender, age, an Index of Relative Advantage and Disadvantage, supply variables, urgency categories, number of diagnoses, type of primary and secondary diagnoses, as well as type of surgical procedures	Women had about 1.5% longer waiting times. However, the difference was not significant
Auteri and Maruotti (2012)	Hospitalisation waiting times from the Italian NHS – between 1999-2000 - Survey data	A two-part model to explain the probability and length of waiting times	Gender, age, education level, job occupation, marital status, regional effects, need or morbidity factors, private insurance	Women were more likely to be submitted to longer waiting times than men, however, there were no significant differences with respect to gender in the probability of waiting
Laudicella et al. (2012)	Patients admitted for elective hip replacement in the English NHS in the financial year 2001/2002 (n=33,709 observations) – Administrative data	Log-normal models to explain the waiting times	Gender, age, income, education level, number of diagnoses, type of primary diagnoses, and hospital-fixed effects	Women had significant 3% shorter waiting times than men for elective hip replacement
Askildsen et al. (2010)	Elective inpatient stays at Norwegian public hospitals from 1999-2005 (n=311,188 observations) – Administrative data	Random effect linear model to explain waiting times and a random effect probit model to explain the probability of excessive waiting times	Gender, age, main chapters in ICD10, number of sub-diagnoses, health region, priority group, hospital type, time trend	Women had shorter waiting times as well as a lower probability of excessive waiting, both significant
Cooper et al. (2009)	Patients submitted to knee replacement, hip replacement, and cataract scheduled surgeries from the English NHS between 1997-2007 (n=3,400,000 observations) – Administrative data	OLS model for each of the three treatments, using the waiting times as the dependent variable	Gender, age, category of deprivation, area type, provider, year	Women had higher waiting times for knee replacements and cataract repair, and men had longer waiting times for hip replacement, all significant

[a] Coronary artery bypass grafting; [a] Percutaneous coronary intervention

As can be observed in Table 1.1, the conclusions on the gender gap are not consensual in the literature on scheduled access. It can be argued that the results depend on the country or health system. However, most importantly, it may depend on data quality (survey or administrative data) or the type of treatment or surgical procedures under analysis, as Cooper et al. (2009) have demonstrated.

Also, the variety of heterogeneity controls and methods used in these studies do not allow us to gain a clear understanding of the sources for the gender gap. Moreover, the literature is still very focused on using the gender as a control variable rather than trying to understand which factors influence the waiting times by gender.

Thus, there are two types of gender gap that need to be addressed and where the literature is not very clear. The first is the "gross gender gap" and corresponds to a difference of averages in waiting times between men and women, without control variables. The second gap corresponds to an "unexplained" or "adjusted" gender gap and consists of the part that is left to be explained, after controlling for a set of variables. Without additional considerations, the existence of the second gap may indicate a behaviour that harms one of the genders.

We opted for analysing all the administrative data on waiting time for scheduled surgery from the Portuguese NHS. To our knowledge, there are no previous gender's studies that include all the administrative data on waiting times, control for so many sources of heterogeneity, including, for instance, all the surgical procedure-fixed effects (with a dummy for each of the approximately 3,000 codes), and measure the factors that explain the gender gap.

Therefore, our study seeks to make a relevant contribution to the literature and health policy because, instead of just addressing the differences in waiting times between men and women, we intend to conduct a more detailed of the sources of the gender gap on surgical treatment, focusing on both "gross" and "adjusted" gender gap.

1.3 Data and Methodology

This study examines waiting times for all patients submitted to surgical treatment in the Portuguese NHS, from 2011 to 2015 using data from all patients registered in SIGIC.

SIGIC data was provided by the Portuguese Central Administration of the Health System (ACSS). Waiting times correspond to the period elapsed from the moment of entry in the list until the patient has been treated.[1]

The descriptive statistics of waiting times across genders presented in Table 1.2 show that women have a higher number of surgical acts and longer waiting times for surgery (in both average and median values).

Table 1.2: Descriptive statistics –Waiting times of operated patients

		Waiting times				
	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
Men	1,145,341 (42.57)	71.36	36.51	95.92	0	3665
Women	1,545,389 (57.43)	75.60	40.00	102.63	0	3707.35
Total	2,690,730 (100.00)	73.80	38.47	99.85	0	3707.35

We start from a basic econometric specification which provides the "gross gender gap" - "the unadjusted gender gap" $\boldsymbol{\beta}^{\text{base}}$ on waiting times between men and women – to understand how the gender influences waiting times:

$$\mathbf{Y} = \boldsymbol{\beta}^{\text{base}}\,\mathbf{G} + \boldsymbol{\varepsilon} \tag{1.1}$$

where $\mathbf{Y}$ corresponds to a vector of waiting times (in logs) and $\mathbf{G}$ corresponds to a gender dummy, in which female is the reference category for gender ($\mathbf{G} = 0$ for females).[2] If $\boldsymbol{\beta}^{\text{base}} = 0$ means that there is no evidence of gender gap and waiting times are randomly distributed across genders while $\boldsymbol{\beta}^{\text{base}} < 0$ indicates that on average waiting times are longer for women and so there is a gender gap favouring men. This conclusion was reversed if $\boldsymbol{\beta}^{\text{base}} > 0$ and now the gender gap would harm men in terms of waiting times.

Adding additional covariates to Eq. 1.1 should not change the estimate of $\boldsymbol{\beta}^{\text{base}}$ unless the effects of these covariates is unevenly distributed across gender. This means that, for example, if waiting times are evenly distributed across gender within hospitals then adding a fixed effect for hospital should not affect the estimate of $\boldsymbol{\beta}^{\text{base}}$.

[1]Since the database is anonymised, we are unable to follow-up the patients to infer whether they were submitted to more than one surgery in the period under analysis.

[2]We employed the logarithmic transformation to deal with skewed data. Since the logarithm of zero is not defined, the waiting times equal zero have been replaced by half of the minimum waiting times when excluding zeros. These observations represent 0.72% of the total sample.

Thus, to understand the sources of the gender gap, we add to Eq. 1.1 all sources of heterogeneity that may be unevenly distributed across gender. That is, we estimate the following econometric model:

$$\mathbf{Y} = \boldsymbol{\beta}^{\text{full}}\,\mathbf{G} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{1.2}$$

where $\boldsymbol{\beta}^{\text{full}}$ corresponds to the "adjusted" or "unexplained" gender gap and $\mathbf{X}$ is a matrix (N x k) containing a set of covariates all of them introduced as fixed effects. If now, $\boldsymbol{\beta}^{\text{full}} = 0$ then it indicates that differences across genders from eq. 1.1 are fully explained by the added covariates. In this case, the source of the gender gap can be traced to the considered heterogeneity sources.

If, however, $\boldsymbol{\beta}^{\text{full}} \neq 0$ it means that there are unexplained differences that remain between men and women and that are not linked to heterogeneity sources that were introduced in the model. Thus, in our approach we try to account for as many sources of heterogeneity as possible.

In line with the literature, we control for the severity. We use the patient's initial priority [3] [4] and patient's cancer indicator. These variables are considered to be relevant for explaining the gender gap since it is argued that women and men have distinct levels of health care utilisation and are diagnosed and treated presenting different levels of illness (Payne, 2009; Perelman et al., 2012). Moreover, we also added fixed-effects to control for the specialty and surgical procedure since they may be associated with a different availability of beds, surgeons operating and for being closely related to the diseases and medical needs inherent to each of the sexes (eg: reproductive function, genetic impact (Payne, 2009)).

We have included fixed-effects for hospitals to control for possible treatment variations between men and women resulting, for instance, from the organizational structure

[3] The clinical priority for surgery corresponds to the severity levels attributed to the patient, based on their clinical situation or need for treatment. Level 1 - the patient can wait up to 270 days for the surgery, or 60 days in the case of an oncological disease (less severe priority level). Level 2 - the surgical treatment cannot exceed more than 60 days or 45 days in case of an oncological disease; Level 3 - surgery has to be carried out within a maximum of 15 days; Level 4 - surgery has to be performed within a maximum of 3 days or during the patient's hospitalisation (most severe priority level) (https://dre.pt/application/conteudo/66807918).

[4] We must note priority level is the best variable we have to measure the severity of the clinical condition, although clinical priority can also be affected by the way patients report their clinical condition.

and human resources (Foss and Sundby, 2003; Verbrugge and Steiner, 1981). Furthermore, we added fixed-effects for municipality to control for the place of residence of the patient and thus to control for socioeconomic status and the specific access to disease prevention and health promotion programmes that differs across municipalities (Lasch et al., 2010).

The variable age of the patient was also introduced to control for the different age-related medical needs (Lasch et al., 2010; Raine, 2000). We chose to introduce this variable as a fixed effect to avoid imposing any parametric constraint on the effect of age on waiting times, meaning that we included a dummy variable for each different value of age.

In addition, age also intends to capture socioeconomic differences between men and women, wherein older women tend to have lower qualifications and income than men, being much more exposed to the risk of poverty (European Commission, 2019).

For instance, the paper of Kaarboe and Carlsen (2014) uses gender, age, and municipality to assign patients to population cells and obtain income and educational levels, given the inability to have the socioeconomic status of each patient. In this line, we estimate an additional model that includes an interaction of the municipality and the patient's age fixed-effects to better control for the socioeconomic status.

We also added the variable year of surgery to capture any possible difference in the evolution of healthcare use across genders. The descriptive statistics can be found in Table 1.3 and in Appendix.

We should note that estimation of Eq. 1.2 is not straightforward.[5] Some of the variables referred to above, such as the surgical procedure, place of residence or interaction between municipality and age-fixed effects, have a large number of values (are of high dimension). The high dimensionality of these variables, makes it difficult to estimate the OLS model using conventional methods.

Thus, we employ the High-Dimensional Fixed effects algorithm to overcome the computational restraints, as proposed by Guimaraes and Portugal (2010). With this approach we are able to obtain the OLS estimates regardless of the number of high-

[5] We include all variables as fixed effects, that is, a dummy variable is created for each category of each variable.

Table 1.3: Descriptive statistics

MEN

		Waiting times				
	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
Priority						
1	845,096 (73.79)	89.73	57.61	103.41	0	3665
2	196,092 (17.12)	27.44	17.35	42.28	0	2064.42
3	62,571 (5.46)	6.89	3	20.27	0	2120.60
4	41,582 (3.63)	2.14	1.33	6.83	0	365.73
Cancer						
Yes	101,604 (8.87)	27.22	20.35	30.80	0	834.39
No	1,043,737 (91.13)	75.66	40.73	98.97	0	3665
Age						
<15 years	102,802 (8.98)	94.58	68.76	91.46	0	1464.38
[15,30[	90,890 (7.94)	80.59	48.50	97.32	0	2329.64
[30,45[	136,499 (11.92)	76.21	42	98.49	0	2476.54
[45,60[	226,443 (19.77)	71.76	35.53	100.80	0	3665
[60,75[	351,033 (30.65)	66.93	32.66	95.74	0	3577.70
>=75 years	237,674 (20.75)	61.18	28.59	88.84	0	3653

WOMEN

		Waiting times				
	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
Priority						
1	1,193,259 (77.21)	91.84	58.38	109.73	0	3707.35
2	237,827 (15.39)	28.01	19.42	42.05	0	2582.62
3	67,711 (4.38)	7.09	2.77	30.51	0	3653.38
4	46,592 (3.01)	2.24	1.33	7.36	0	596
Cancer						
Yes	117,253 (7.59)	24.29	18.46	33.20	0	3653.38
No	1,428,136 (92.41)	79.82	44.38	105.22	0	3707.35
Age						
<15 years	62,012 (4.01)	90.54	61.51	93.46	0	1288.37
[15,30[	91,485 (5.92)	78.02	43.38	101.77	0	2346.32
[30,45[	263,826 (17.07)	74.70	41.43	103.53	0	3707.35
[45,60[	389,897 (25.23)	81.91	44.69	110.28	0	2787.38
[60,75[	416,843 (26.97)	77.80	40	105.37	0	3653.38
>=75 years	321,326 (20.79)	62.25	28.72	88.21	0	3639.67

dimensional fixed effects that are considered.

In addition, we also seek to investigate which factors explain the gender gap in access to surgical treatment and to what extent. To observe the contribution of each of the covariates to the explained gender gap ($\widehat{\boldsymbol{\delta}}^{\text{gender}} = \widehat{\boldsymbol{\beta}}^{\text{base}} - \widehat{\boldsymbol{\beta}}^{\text{full}}$), we use the unambiguous decomposition proposed by Gelbach (2016). Following Gelbach (2016), and Cardoso et al. (2016), the explained gender gap, $\widehat{\boldsymbol{\delta}}^{\text{gender}}$, can be decomposed according to Eq. 1.3.

$$\widehat{\boldsymbol{\delta}}^{\text{gender}} = \widehat{\boldsymbol{\theta}}_1^{\text{year}} + \widehat{\boldsymbol{\theta}}_2^{\text{hospital}} + \widehat{\boldsymbol{\theta}}_3^{\text{municipality}} + \widehat{\boldsymbol{\theta}}_4^{\text{procedure}} + \widehat{\boldsymbol{\theta}}_5^{\text{priority}} + \widehat{\boldsymbol{\theta}}_6^{\text{age}} + \widehat{\boldsymbol{\theta}}_7^{\text{speciality}} + \widehat{\boldsymbol{\theta}}_{\mathbf{8}}^{\text{cancer}} \tag{1.3}$$

The coefficients $\widehat{\boldsymbol{\theta}}_1^{\text{year}}, \widehat{\boldsymbol{\theta}}_2^{\text{hospital}}, \ldots, \widehat{\boldsymbol{\theta}}_8^{\text{cancer}}$ are computed by OLS according to the following equations and correspond to the contribution of each group of covariates to the explained part of the gender gap. This procedure follows the methodology of Gelbach (2016).

$$\widehat{\mathbf{year}}_{\text{FE}} = \widehat{\boldsymbol{\theta}}_1^{\text{year}} * \mathbf{G} \tag{1.4}$$

$$\widehat{\mathbf{hospital}}_{\text{FE}} = \widehat{\boldsymbol{\theta}}_2^{\text{hospital}} * \mathbf{G} \tag{1.5}$$

(...)

$$\widehat{\mathbf{cancer}}_{\text{FE}} = \widehat{\boldsymbol{\theta}}_8^{\text{cancer}} * \mathbf{G} \tag{1.11}$$

where $\widehat{\mathbf{year}}_{\text{FE}}$, $\widehat{\mathbf{hospital}}_{\text{FE}}$, ..., $\widehat{\mathbf{cancer}}_{\text{FE}}$ are vectors of the estimates for the covariates obtained by the estimation of eq. 1.2. For more details on the implementation of Gelbach's decomposition in a similar context see Cardoso et al. (2016). Stata 14 software was employed for the econometric analysis.

1.4 Results

Table 1.4 shows the estimation of eq. 1.1 and eq. 1.2, respectively. Eq. 1.2 was estimated using the Stata command "reghdfe" that implements the algorithm of Correia (2017). The heteroskedasticity-robust standard errors are shown in parenthesis.

The first column respects the estimation of base model, the second column concerns the estimation of eq. 1.2 in which all covariates are included without interactions, while the third column shows the estimation of eq. 1.2 with the interaction between the municipality of residence and patient's age fixed effects for a better control for the patient's socioeconomic status.

Table 1.4: Estimation of the base and full model

	Eq. 1.1	Eq. 1.2	Eq. 1.2 - with interaction
$\widehat{\boldsymbol{\beta}}$ ˆ	-0.1059***	-0.0313***	-0.0318***
	(0.0027)	(0.0025)	(0.0025)
Observations	2,690,730	2,689,204	2,687,797
Covariates	No	Yes	Yes
Year		X	X
Hospital		X	X
Municipality		X	
Procedure code		X	X
Priority		X	X
Age		X	
Speciality		X	X
Cancer		X	X
Municipality* Age			X

$^{***}p < 0.01$

The base model estimation (eq. 1.1) shows that men on average wait less time, with a gross gender gap of minus 10.6 log points (corresponding to minus 10%) [6] of waiting time. After controlling for multiple sources of observed and unobserved heterogeneity in eq. 1.2 the gap reduces to minus 3.1 log points (-3.1%) showing that a significant but unexplained difference in the waiting times of men and women still persists.

The inclusion of the interaction between the municipality and patient's age fixed effects is not relevant in changing the unexplained gender gap (in comparison with

[6] The exact percentage difference in predicted waiting times between men and women is then computed: $100 \cdot \left(\exp\left(\widehat{\beta}_1\right) - 1\right) = 100 \cdot (\exp(-0.1059) - 1) = -10.05\%$.

Table 1.5: Gelbach's decomposition of the explained gender gap

Variable	Contribution	Coefficient	Contribution (%)
YearFE	$\widehat{\boldsymbol{\theta}}_1^{\text{year}}$	0.0026***	-3.50
		(0.0002)	
HospitalFE	$\widehat{\boldsymbol{\theta}}_2^{\text{hospital}}$	-0.0170***	22.91
		(0.0005)	
MunicipalityFE	$\widehat{\boldsymbol{\theta}}_3^{\text{municipality}}$	-0.0021***	2.83
		(0.0001)	
ProcedureFE	$\widehat{\boldsymbol{\theta}}_4^{\text{procedure}}$	-0.0124***	16.71
		(0.0008)	
PriorityFE	$\widehat{\boldsymbol{\theta}}_5^{\text{priority}}$	-0.0582***	78.44
		(0.0009)	
AgeFE	$\widehat{\boldsymbol{\theta}}_6^{\text{age}}$	0.0181***	-24.39
		(0.0001)	
SpecialityFE	$\widehat{\boldsymbol{\theta}}_7^{\text{speciality}}$	-0.0016***	2.16
		(0.0004)	
CancerFE	$\widehat{\boldsymbol{\theta}}_8^{\text{cancer}}$	-0.0036***	4.85
		(0.0001)	
TOTAL	$\widehat{\boldsymbol{\delta}}^{\text{gender}}$	-0.0742	100

$^{***}p < 0.01$, NOTE: The robust standard errors are in parenthesis

specification of column 2), and therefore we opted for including all the covariates separately for the next estimations.

Table 1.5 uses Gelbach's decomposition to show the contribution of each source of heterogeneity (covariate) to the explained gender gap on waiting times (obtained from equations 1.4-1.11).

As expected, adding all the coefficients in Table 1.5, we get the value of minus 7.4 log points, corresponding to the $\widehat{\boldsymbol{\delta}}^{\text{gender}}$. The table shows that patient's initial priority is the covariate that contributes most to the explained gap contributing with minus 5.8 log points, indicating that a large part of the gender gap can be explained by the fact that men have more severe priorities (which have shorter waiting times).

Hospital-fixed effects contribute with about minus 1.7 log points to the explained gender gap followed by surgical procedures-fixed effects with minus 1.2 log points. These later results seem to indicate that women are slightly more likely to have surgical procedures associated with longer waiting times while the distribution of men across hospitals tends to favour those with shorter average waiting times.

Age-fixed effects present an opposite sign, with 1.8 log point. One may conclude that women's treatment is, on average, more associated with ages with shorter waiting times.

Despite having less relevance in the explained gender gap, the remaining fixed effects show that there is a higher probability of women to be treated in municipalities with longer waiting times. Men are more likely to be reported with cancer (shorter average waiting times) and be treated in specialities with smaller waiting times. The results also show there is a higher concentration of women operated in years with shorter waiting time.

Sensitivity analysis

We performed some robustness checks to observe the consistency of the gender gap previously identified. First, we estimate the equation 2 separately for each of the most frequent medical specialities, as well as for different age groups (Table 1.6 and Table 1.7, respectively). We intend to observe the gender gap pattern despite the specificities of each speciality. Moreover, observing the gender gap by age groups with the municipality fixed effects gives higher control for socioeconomic status, since the age factor is said to be crucial in explaining gender differences due to income or educational background.

Table 1.6 shows a pattern in which women have, on average, longer waiting times for surgery. Although otolaryngology and dermatology present an opposite sign, the coefficients are not statistically significant. In Table 1.7, we can observe a similar pattern wherein women have longer waiting times. The age group below 15 years presents an opposite sign (without statistical significance).

We performed other estimations with subsamples of the observations, to exclude observations that might be unduly biasing the results. In scenario A, we excluded the top 10% of waiting times for surgery, because there could be an abnormal number of women in those outlier observations. In scenario B, we eliminated patients who were on the waiting list for less than one day, because those patients who were admitted through the emergency department could be treated differently.

In scenario C, we perform an additional check to see the impact on the unexplained

Table 1.6: Gender gap by medical speciality

Speciality	$\widehat{\boldsymbol{\beta}}^{\text{full}}$
Ophthalmology	-0.0187***
General surgery	-0.0078
Orthopaedic	-0.0214***
Otolaryngology	0.0017
Urology	-0.0492***
Plastic surgery and reconstruction	-0.0515***
Vascular surgery	-0.0221
Dermatology	0.0204
Neurosurgery	-0.0569***
Stomatology	-0.0467**
Cardiothoracic surgery	-0.0369*

$^{***}p < 0.01$ $^{**}p < 0.05$, $^{*}p < 0.10$

Table 1.7: Gender gap by age group

Age-group	$\widehat{\boldsymbol{\beta}}^{\text{full}}$
<15 years	0.0118
[15,30[	-0.035***
[30,45[	-0.0252***
[45,60[	-0.0396***
[60,75[	-0.0407***
>=75 years	-0.0072

$^{***}p < 0.01$

Table 1.8: Estimation with subsamples of observations

Scenario	$\widehat{\boldsymbol{\beta}}^{\text{full}}$
A	-0.0252***
B	-0.0318***
C	[-0.0535, -0.052]***

$^{***}p < 0.01$

gender gap if we focused on a number of categories for a given variable, due to computational constraints (for instance), instead of including them all with the most flexible parametric specification, as we have estimated. To exemplify, we took the surgical procedure variable (variable with the largest number of categories), and we included a dummy for each of the 100 most common procedures and coded the remaining categories as "others". We have also tested for the 150 and 200 most common procedures. Table 1.8 shows the estimates.

The results confirm that the gender gap is consistent across subsamples – in all scenarios women have, on average, longer waiting times. Scenario C shows the gender gap is overestimated when focusing on a specific number of surgical procedures. This result reveals that a more flexible specification guarantees a more accurate estimate for the unexplained gender gap, so the HDFE model may play an important role when the number of categories makes impossible the estimation using conventional estimation methods.

1.5 Discussion

The use of a methodology suitable for estimation of high-dimensional fixed effects (HDFE) models allowed us to control for a set of covariates that would not be possible to include in the model using the conventional approach (e.g., municipality and age interaction). In fact, we tried to use the standard approach to estimate an OLS model, but we ran into computer memory problems.

Thus, we started with a 10% gross gender gap, and we found an unexplained gender gap in which men wait only 3.1% less time than women when controlling for a set of covariates. This represents only a 1-day difference between men and women, which is much smaller than previous literature has suggested. However, it is a significant unexplained difference that cannot be related to observed differences across genders for any of the covariates included in the full model.

This result could be an indication of "pure" discrimination towards women. However, there may be other factors for which we are not controlling, and which could explain the result. In fact, this is an open question.

Furthermore, the application of Gelbach's decomposition allowed us to disentangle the contribution of each factor to the explained gender gap of 7.4 log points. It showed that the patient's initial priority is the variable that explains most of that disparity, followed by hospital-fixed effects. This result suggests that men are classified as having more severe priorities, which affects waiting times since higher degrees of illness have shorter waiting times. This result may be explained by the literature, that found men have a lower healthcare utilisation and they display a worse clinical condition when getting access to treatment (Payne, 2009).

However, if there are substantial variations in the way men and women present illness symptoms and communicate their clinical condition (Alspach, 2012), the chance of the patient's prioritisation suffering from gender bias cannot be excluded. Also, the hypothesis of gender discrimination in patient prioritisation cannot be ruled out. It could be justified, for instance, by the fact that doctors may assume that men still use health care later than women and that they must be treated early to avoid medical problems for the potential delay. Men can also still be seen by doctors as the primary financial support of the families, which can lead to higher priorities for surgery to return more quickly to their professional activity.

The hospital-fixed effects are the second factor that contributes most to the gender gap, which corroborates the hypothesis that there may be gender biases in the procedures adopted by some hospitals. It means, that controlling for all other variables, there are hospital specificities that cause men to have shorter waiting times.

It is, thus, suggested the need for hospital gender-sensitive health indicators to increase the transparency and assess its comparability and progress, as well as audits of hospital activity to identify the reasons for the reported differentials.

1.6 Conclusion

This study analyses the gender gap in waiting times for scheduled surgery in the Portuguese NHS. We used data from 2011 to 2015 and a model that allowed us to account for multiple sources of heterogeneity using an highly flexible parametric specification to obtain an estimate for the adjusted gender gap.

We found that a small but significant gender bias persists indicating that women wait longer for surgery, although this bias is much smaller than the one obtained when those factors were not considered. The decomposition of the explained gender gap confirms a pattern that seems to disadvantage women.

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Appendix

Appendix shows the descriptive statistics for the variables: year; hospital; municipality; procedure code; and speciality.

For the sake of simplicity, the tables show the first 5 categories (with higher frequencies) for the variables: hospital; municipality; procedure code; and speciality. However, all categories are considered in the study.

Table A1.1: Descriptive statistics - Year

MEN

		Waiting times				
Year	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
2011	210,954 (18.42)	67.33	33	95.11	0	3665
2012	225,311 (19.67)	70.20	34.42	98.61	0	2272.34
2013	232,157 (20.27)	69.58	35.75	96.64	0	2237.42
2014	236,329 (20.63)	72.67	39.43	94.89	0	3577.70
2015	240,590 (21.01)	76.43	41.50	94.12	0	2388.47

WOMEN

		Waiting times				
Year	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
2011	290,793 (18.82)	72.11	36.43	103.73	0	3639.67
2012	308,951 (19.99)	74.76	37.38	106.14	0	3681.35
2013	312,214 (20.20)	73.72	38.59	104.25	0	3707.35
2014	313,634 (20.29)	76.42	42.42	100.24	0	2620.34
2015	319,797 (20.69)	80.61	44.50	98.60	0	2132.44

Table A1.2: Descriptive statistics - Hospital*

MEN

		Waiting times				
Hospital (sorted)	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
CH São João	81,591 (7.12)	57.26	20.77	71.42	0	556.89
CH Universitario Coimbra	80,145 (7.00)	75.36	22.48	136.83	0	3577.7
CH Lisboa Central	75,970 (6.63)	67.16	29.49	96.78	0	3653
CH Porto	55,419 (4.84)	73.36	41.72	88.31	0	1468
CH Lisboa Norte	52,894 (4.62)	62.13	28.57	96.95	0	1966.56

WOMEN

		Waiting times				
Hospital (sorted)	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
CH. Universitario Coimbra	107,613 (6.96)	82.42	32.81	138.16	0	2620.34
CH São João	100,477 (6.50)	59.68	25.41	72.9	0	643.44
CH Lisboa Central	95,967 (6.21)	71.3	32.38	109.58	0	1570.37
CH Porto	74,152 (4.80)	72.98	41.70	90.98	0	1319
H Braga	66,470 (4.30)	59.97	31.69	84.85	0	1828.54

*Total number of categories=61

Table A1.3: Descriptive statistics - Municipality*

MEN

		Waiting times				
Municipality (sorted)	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
Lisboa	67,352 (5.88)	59.32	29.56	85.12	0	1706.34
Amadora	41,899 (3.66)	52.51	20.79	75.58	0	1334.38
Vila Nova de Gaia	40,960 (3.58)	67.38	42.5	79.13	0	2329.64
Porto	37,894 (3.31)	59.93	29.55	77.35	0	2442.34
Braga	31,873 (2.78)	58.88	34.65	79.95	0	1423.46

WOMEN

		Waiting times				
Municipality (sorted)	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
Lisboa	94,337 (6.10)	61.06	29.77	93.05	0	3653.38
Vila Nova de Gaia	55,623 (3.60)	72.29	44.65	93.26	0	2787.38
Porto	55,542 (3.59)	64.14	31.42	96.38	0	2673.59
Amadora	45,633 (2.95)	58.22	21.62	91.33	0	1486.77
Braga	43,588 (2.82)	61.55	32.77	88.37	0	1828.54

*Total number of categories=308

Table A1.4: Descriptive statistics - Procedure code*

MEN

Surgical procedure (sorted)	Obs. (%)	Waiting times Mean	Median	Std. Dev.	Min.	Max.
Phacoemulsification and aspiration of cataract	119,433 (10.43)	85.52	64.7	83.31	0	3577.7
Local excision or destruction of lesion or tissue of skin and subcutaneous tissue	44,895 (3.92)	58.12	35.44	70.22	0	1966.56
Radical excision of skin lesion	36,136 (3.16)	40.66	22.63	54.49	0	1425.4
Operation on vitreous	34,581 (3.02)	20.87	13.44	28.31	0	1272.69
Circumcision	24,689 (2.16)	100.55	76.36	90.11	0	1292.63

WOMEN

Surgical procedure (sorted)	Obs. (%)	Waiting times Mean	Median	Std. Dev.	Min.	Max.
Phacoemulsification and aspiration of cataract	188,868 (12.22)	87.56	67.43	83.51	0	1611.71
Carpal tunnel release	54,487 (3.53)	85.78	57.35	84.6	0	1502.41
Local excision or destruction of lesion or tissue of skin and subcutaneous tissue	53,045 (3.43)	58.6	35.42	72.81	0	2028.5
Ligation and stripping of varicose veins, lower limb veins	52,067 (3.37)	124.38	89.38	134.76	0	2620.34
Laparoscopic cholecystectomy	45,150 (2.92)	109.59	76.85	124.19	0	2010.47

*Total number of categories=3464

Table A1.5: Descriptive statistics - Speciality*

MEN

		Waiting times				
Speciality (sorted)	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
General surgery	285,595 (24.76)	75.39	42.61	97.89	0	2388.47
Ophthalmology	258,357 (22.56)	60.12	31.43	77.34	0	3577.7
Orthopaedic	151,406 (13.22)	90.66	43	121.26	0	3665
Urology	115,340 (10.07)	74.65	45.71	91.97	0	2120.6
Otolaryngology	95,117 (8.30)	103.23	74.72	100.94	0	1303.43

WOMEN

		Waiting times				
Speciality (sorted)	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
Ophthalmology	347,985 (22.52)	66.9	37.73	80.26	0	1996.6
General surgery	279,838 (18.11)	76	39	109.83	0	2582.62
Orthopaedic	257,591 (16.67)	94.88	49.49	119.75	0	3639.67
Gynaecology	233,986 (15.14)	60.38	40.38	69.71	0	3707.35
Plastic and reconstructive surgery	85,843 (5.55)	90.19	41.36	137.37	0	3681.35

*Total number of categories=43

Chapter 2

Surgery access, cancellations and patients' prioritisation in the Portuguese NHS

Abstract

Equity in access to scheduled surgery and waiting times prioritisation policies aimed at increasing the efficiency of the waiting lists have been topics of attention of researchers and decision-makers on health. Most studies analyse the number of days that patients wait for surgery for patients that underwent surgery. This fact causes them to ignore patients that have been on the waiting list but have not benefited from surgery. Thus, this study contributes to the existing literature on waiting lists by analysing cancellations along with surgery episodes. We use a database comprising all scheduled surgeries from the Portuguese NHS from 2011 to 2015 (around 3 million observations) and estimate survival models (Cox, Weibull, and Piecewise exponential models) to explain waiting times. Since the cancellation rate is significant (around 14%), it may have a considerable impact on results. If we restrict the model to the patients that were submitted to surgery we find that the excluding cancellations leads to different results. Our approach provides a more comprehensive understanding of the impact that several factors have on overall access to scheduled surgery. Furthermore, we found some inequalities and priority noncompliance patterns in the different motivations for cancellations. Altogether, the results provide some clues that could be used in an effort to make reforms that increase equity and improve prioritisation of the Portuguese NHS.

Keywords: scheduled surgery, access, prioritisation, cancellations, survival models, Portugal

JEL Classification: *I14*, *C01*

2.1 Introduction

Waiting lists and waiting times for scheduled surgery are commonly associated with developed countries and public health systems (Siciliani and Hurst, 2005). These health systems are characterised by reduced co-payments which originate an excess of demand, causing more prolonged waiting times and the growth of surgery lists.

If, on the one hand, it is claimed that longer waiting times are a mechanism of rationing, on the other, waiting times are seen as a barrier in the access to surgical treatment (Landi et al., 2018). Thus, there has been a wide-ranging discussion concerning the equity in access to scheduled surgery that focuses on particular patients' characteristics (e.g. age, gender, socioeconomic status, etc) (Cima et al., 2018; Cooper et al., 2009; Landi et al., 2018; Laudicella et al., 2012).

What is clear from the literature is that, in the absence of any discrimination, the severity of patient's clinical condition should be the only factor able to explain differences in waiting times among patients (Laudicella et al., 2012). Thus, the prioritisation for surgery should play a central role in detecting the most severe cases (Askildsen et al., 2010; Gravelle and Siciliani, 2008). By identifying the factors that may explain variations in waiting times, one hopes to gain greater awareness for the design of specific policies aimed at increasing equity and fairness in the access to healthcare.

However, a substantial part of the literature on waiting times for scheduled surgery has focused, specifically, on patients that have been treated. These studies disregard cancellations – surgeries that were scheduled to happen but for some reason were cancelled. Cancellations may be motivated by many reasons and may have several consequences for the patient's health, both physical and emotional. They also may raise questions about hospital efficiency (Cookson et al., 2017; Hovlid et al., 2012). In our view, to grasp a better understanding of the factors affecting access to surgery one must take into account the full picture and incorporate cancellations in the analysis, particularly if we are willing to draw any policy conclusion.

Take, for instance, the spatial distribution in waiting times across the country. If in some municipalities the longer waiting times are leading patients to cancel more surgeries then the actual waiting times for surgery in those municipalities will be undervalued. Thus, policies implemented based on the waiting times of operated patients may be inadequate because inequalities in access are underestimated.

One can discuss whether the inclusion of the cancelled episodes would be irrelevant for health systems with reduced cancellations rates. However, that is not the case for the Portuguese National Health Service where for the period under analysis spanning from 2011 to 2015 the cancellation rate was 14.7%.

Thus, in this study, we will use all available information, which includes surgical procedures along with cancellations, to study the equity in access to scheduled surgery and to understand the impact of patient's prioritisation. Our study uses information on all scheduled surgeries on the Portuguese NHS between 2011 and 2015. This amounts to around 3 million observations.

We estimate survival models that include the censored data introduced by cancellations. We also study how the estimates vary according to the methodology, i.e., how they change with the inclusion or non-inclusion of cancellation episodes.

Furthermore, we analyse in detail cancellations. The objective here is to identify groups that are more likely to have different kinds of cancellations and also to assess the impact of priority noncompliance.

The rest of this paper is organised as follows. In section 2, we provide a brief review of the relevant literature. Section 3 describes the methodology used in this paper. Our results are presented in section 4. Section 5 analyses the motivations for cancellation and section 6 discusses the results. Section 7 presents the main conclusions.

2.2 Background

Cancellations for surgical treatment correspond to patients who left the waiting list before being subjected to surgery. Al Talalwah and McIltrot (2018) developed a literature review on cancellations for surgery and found cancellations rates ranged between 0.5 and 39%.

Although the literature on cancellations is vast, a substantial part of these studies has focused on statistical analysis of specific clinical conditions and/or motivations for cancelling (Bamashmus et al., 2010; Caesar et al., 2014; Chang et al., 2014; Dimitriadis et al., 2013; Ezike et al., 2011; Kumar and Gandhi, 2012; Sanjay et al., 2007).

On the other hand, the literature on waiting times to scheduled treatment is still very focused on operated patients. See, for instance, the studies of Laudicella et al. (2012), Cooper et al. (2009), Johar et al. (2013), Landi et al. (2018) that evaluated the factors besides the severity of the patient's clinical condition that might influence the access to treatment. The authors showed that patients' specific socioeconomic and demographic characteristics influence the waiting times. Laudicella et al. (2012) found that waiting times for patients admitted for hip replacement in English NHS are shorter for the elderly and that men have longer waiting times compared with women.

An identical finding was obtained by Cooper et al. (2009) for patients submitted to the hip replacement. On the contrary, Johar et al. (2013) showed longer waiting times for older patients, and also reported that men wait less time than women in New South Wales (Australia). Landi et al. (2018) concluded that gender and age were not relevant in explaining waiting times for elective surgery for the Italian NHS.

Studies as Askildsen et al. (2010), Gutacker et al. (2016), Johar (2014), Januleviciute et al. (2013), Askildsen et al. (2011), Dimakou et al. (2009) estimate how patients are prioritised on the waiting list. Askildsen et al. (2010) analysed the impact of the Norwegian hospital reform of 2002 on prioritisation practices. Using five prioritisation groups, defined by the recommended maximum waiting times, they did not find an improvement in the prioritisation practices standardisation across the country. Gutacker et al. (2016) found hip and knee replacement patients in English NHS are prioritised according to their severity level, although the authors noticed prioritisation is modest.

Johar (2014) showed waiting list prioritisation guidelines in Australia has not produced prioritisation behaviours among doctors while analysing the behaviour before and after the guideline implementation. Askildsen et al. (2011) compare actual waiting times with the recommended maximum waiting times (by medical guidelines) in Norway, and they noticed that patients with more severe health conditions had too low priority in comparison to patients with lower priority. Januleviciute et al. (2013) evaluated the impact of "blanket" and "vertical" prioritisation policies in Scotland and Norway, respectively. The results showed that, for both reforms, patients with lower priorities benefited more. In Norway, this result was made at the expense of longer waiting times for patients with higher priorities. Dimakou et al. (2009) analysed the impact of government targets on waiting times in English NHS. They found that there was an increased probability of surgery close to waiting times targets and that shorter targets lead to a reduction in waiting times.

An open question in this literature is whether results on inequalities and prioritisation patterns would be the same if cancellations were added. As noted earlier cancellations do not refer to completed observations because they are associated with premature exits from the waiting list. Thus, those observations can be understood as censored data that takes place when "incomplete information is available about the survival time of some individuals" (Leung et al., 1997) or "a subject in the study withdraws prematurely" (Cleves et al., 2016). Focusing on completed observations and dropping censored episodes is, in fact, a standard procedure when we are in the presence of censored data. However, this procedure can lead to sample selection problems and produce inconsistent estimators (Leung et al., 1997; Wooldridge, 2002) if we aim at understanding the impact on waiting times for all scheduled surgeries.

McIntosh et al. (2012), Cookson et al. (2013) and Cookson et al. (2017) are part of the reduced literature that analysed cancellations along with surgery episodes. The authors evaluated which factors contributed to last-minute cancellations in scheduled surgery in English NHS and employed binary outcome models with the dependent variable coded according to the cancelled or operated event. However, unlike us, their objective was merely to look at factors affecting the decision to cancel surgery. We, on the other hand, intend to analyse the impact of a set of variables on the time-to-event (surgery) adjusting for censored observations (cancellations) using survival models (Cleves et al., 2016).

Thus, our contribute to the literature is twofold. First, we hope to better understand which factors impact on waiting time to surgery and thus provide a valid insight on inequalities that may exist and which may not be appropriately evaluated with the exclusive use of episodes of surgery. Second, we will also look in more detail to the motivations for cancellation and thus add to recent literature regarding the study of the Portuguese prioritisation in the scheduled surgery.

2.3 Data and Methodology

2.3.1 Data

In this paper, we evaluate the administrative data for scheduled surgery for the Portuguese NHS from 2011 to 2015.[1] The database includes episodes of surgery and cancellation episodes as well. The waiting times correspond to the period elapsed from the moment of entry in the list until the patient has been treated or has left the list by cancellation.

Table 2.1 shows the distribution of the waiting times by surgery and cancellation. As can be seen episodes of surgery are more frequent in the first month of entry into the list but cancellation frequency is higher for the longer waiting times.

Table 2.2 presents the distribution of surgeries and cancellations by the patient's priority, as well as the description of the rules to be applied by the NHS to categorise the level of priority applied to each patient. We can observe that the cancellation rate is higher for priorities considered to be less severe. This result was expected in the sense that higher priorities require a timelier surgical treatment. However, both priority levels 3 and 4 have still a cancellation rate of around 8%.

Figure 2.1 displays the plot of Kaplan-Meier cumulative failure estimates. The vertical axis corresponds to the estimated probability of surgery occurring within a specific time (for all our sample's individuals), and the horizontal axis is the number of days from the moment of entry into the list.[2] The likelihood of surgery occurrence starts, as expected, from zero and monotonically increases to one with the highest increases in the probability of surgery in the first weeks after entrance.

It is then essential to infer to what extent the characteristics of patients and the prioritisation on the Portuguese NHS have been relevant in access to surgery.

Thus, in a preliminary analysis we look at the effect of patient's age, gender, cancer indicator as well as the patient's prioritisation in access to surgery. Figure 2.2 shows the Kaplan-Meier cumulative failures estimates stratified by these variables. For age

[1] The administrative data were obtained from SIGIC, provided by the Portuguese Central Administration of the Health System (ACSS).

[2] We restrict the graph to $t \leqslant 365$ days to simplify the analysis.

Table 2.1: Distribution of the waiting times by surgery and cancellation

Days	Surgery	Cancellation
<=1	188,413 (7%)	17,073 (3.66%)
]1-30]	995,476 (37%)	83,584 (17.92%)
]30-90]	736,387 (27.37%)	86,815 (18.61%)
>90	770,454 (28.63%)	278,966 (59.81%)
TOTAL	2,690,730 (100%)	466,438 (100%)

Table 2.2: Distribution of surgery and cancellation – by priority

Priority	Description*	Surgery	Cancellation	Cancellation rate (%)
1	Waiting time up to 270 days for the surgery, or 60 days in the case of an oncological disease	2,038,355	399,232	16.38
2	The surgical treatment cannot exceed more than 60 days or 45 days in case of an oncological disease	433,919	48,476	10.05
3	Surgery has to be carried out within a maximum of 15 days	130,282	11,144	7.88
4	Surgery has to be performed within a maximum of 3 days or during the patient's hospitalisation	88,174	7,586	7.92

* Diário da República (2015)

Figure 2.1: Kaplan-Meier failure estimate

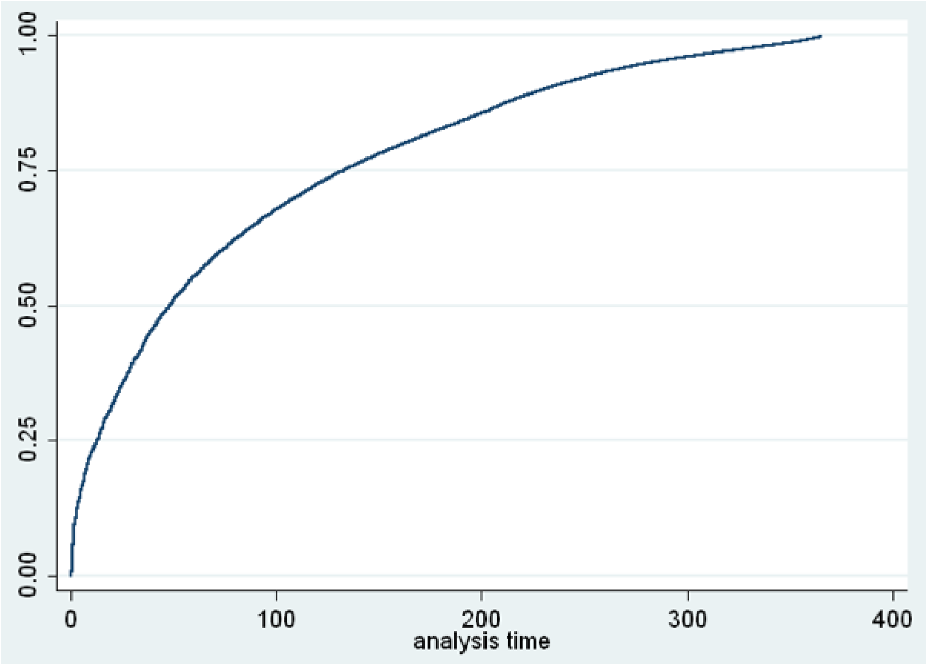
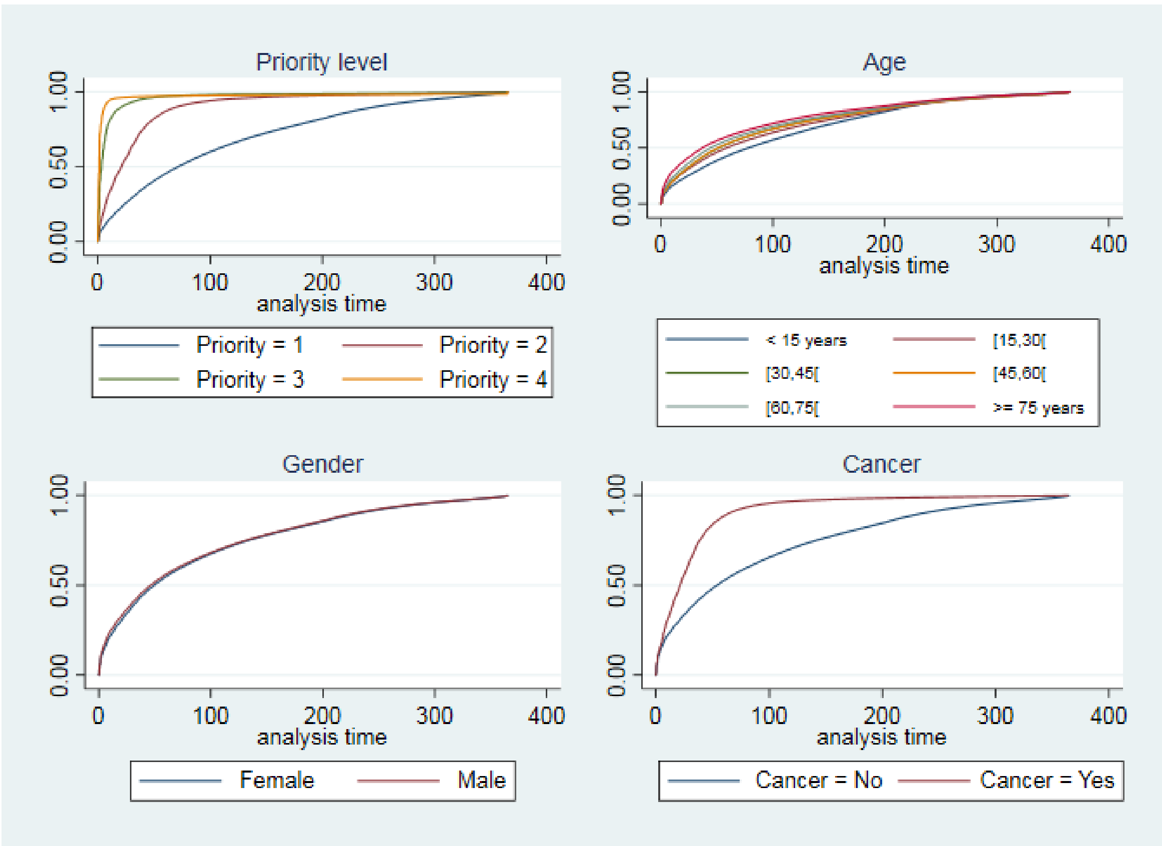


Figure 2.2: Kaplan-Meier failure estimate by priority, age, gender, and cancer



we created six groups as follows: below 15 years old; from 15 to 29; from 30 to 44; from 45 to 59; from 60 to 74; above 75 years. The figures show that priority level exhibits

Table 2.3: Descriptive statistics of waiting times for surgery

		Waiting times				
Variable	Obs. (%)	Mean	Median	Std. Dev.	Min	Max
Gender						
Female	1,545,389 (57.43%)	75.60	40	102.63	0	3707.35
Male	1,145,341 (42.57%)	71.36	36.51	95.92	0	3665
Cancer						
Yes	218,857 (8.13%)	25.60	19.38	32.15	0	3653.38
No	2,471,873 (91.87%)	78.06	42.71	102.65	0	3707.35
Priority						
1	2,038,355 (75.75%)	90.97	57.83	107.16	0	3707.35
2	433,919 (16.13%)	27.75	18.43	42.15	0	2582.52
3	130,282 (4.84%)	6.99	3.00	26.10	0	3653.38
4	88,174 (3.28%)	2.19	1.33	7.12	0	596
Age groups						
<15 years	164,814 (6.13%)	93.06	65.67	92.24	0	1464.38
[15,30[	182,375 (6.78%)	79.30	45.52	99.58	0	2346.32
[30,45[	400,325 (14.88%)	75.21	41.51	101.84	0	3707.35
[45,60[	616,340 (22.91%)	78.18	41.58	107.00	0	3665.00
[60,75[	767,876 (28.54%)	72.83	36.41	101.22	0	3653.38
>=75 years	559,000 (20.78%)	61.79	28.67	88.48	0	3653.00

the largest differences in the likelihood of surgery, followed by the patients referred with cancer. This means that priorities associated with more severe clinical conditions, as well as patients with cancer, have shorter waiting times for surgery. Age groups also seem to explain differences in access, where older patients have seemingly shorter waiting times. The differences in access caused by gender are not so apparent with the curves of both sexes almost overlapping. Table 2.3 reports descriptive statistics.

2.3.2 Survival Models

In this section we estimate survival models where we simultaneously account for patient characteristics such as gender, age, priority level and cancer while controlling for an additional set of variables such as hospital, speciality, surgical procedure or place of residence. Thus, we introduce several additional controls that account for known sources of heterogeneity. We include dummy variables for the speciality and surgical procedures to account for the specificities of surgical treatment.[3] We add hospital dum-

[3]Since there are thousands of categories on surgical procedures, we cannot control for all the procedures categories due to computational constraints and to avoid the incidental parameter bias as well.

mies intended to capture differences in waiting times due to the organisational structure or other factors which may be specific to each hospital. The patient's place of residence (municipality) is incorporated to capture regional disparities such as the average income, education level, access to health services that may impact waiting times. Finally, we add the variable "year" intended to capture nationwide policy decisions that may affect all waiting times alike.

The survival models to be estimated to analyse the access to surgery are proportional hazard models, where surgery is the event of interest and cancellation corresponds to censored observations. The general specification is given by:

$$h(t) = h_0(t) \cdot \exp(\mathbf{X}\boldsymbol{\beta}) \tag{2.1}$$

where $h(t)$ is the hazard rate of the surgery, that is also known as the instantaneous rate of an event occurrence. $\mathbf{X}$ corresponds to a vector of covariates (gender, age, priority, cancer, speciality, procedure code, year, hospital, municipality of residence), $\boldsymbol{\beta}$ are the coefficients to be estimated and $h_0(t)$ is the baseline hazard.

The parameters $\boldsymbol{\beta}$ indicate how the risk (likelihood) of surgery increases/decreases according to the degree of exposure. Take, for instance, the estimate for male. If $\beta_{male} > 1$, it can be concluded that, conditional on all other variables, men are more likely to be submitted to surgery, and therefore, they have lower waiting times than women.

The baseline hazard function $h_0(t)$ may be modelled using different specifications. The Weibull model is a popular parametric method in survival analysis (Cleves et al., 2016; Lai, 2014). It assumes the following specification for $h_0(t)$ (Cleves et al., 2016):

$$h_0(t) = \rho t^{\rho-1} \exp\left(\beta_0\right) \tag{2.2}$$

Replacing in the hazard function (eq. 2.1), we obtain:

$$h(t) = \rho t^{\rho-1} \cdot \exp\left(\beta_0\right) \cdot \exp(\mathbf{X}\boldsymbol{\beta}) \tag{2.3}$$

We used dummy variables for the 300 most common surgical procedures, and we coded the rest as "others".

When $\rho > 1$, the hazard function is monotonically increasing, meaning the risk of failure increases over time. When $\rho < 1$ the hazard is monotonically decreasing where the risk of failure decreases over time. Finally, the Weibull function is reduced to the exponential model when $\rho = 1$. In this case the risk of failure is constant over time (Cleves et al., 2016; Jones, 2000). Although the Weibull model has greater flexibility, particularly concerning the exponential model, and allows for the estimation of the baseline hazard, its main limitation lies in the hazard monotonicity (Lai, 2014). At a given interval, the hazard function may be decreasing, and in a subsequent time may be increasing. This means that imposing a Weibull specification without further considerations may be too restrictive.

Nevertheless, there are some models that account for non-monotone hazards. The Piecewise exponential (PWE) model is an example of such models (Sá et al., 2007). This model splits time into different intervals, assuming that the hazard rate is constant within each one, but may vary between ranges (J).

$$h_j(t) = \exp\left(\beta_0\right)_j \cdot \exp(\mathbf{X}\boldsymbol{\beta}) \tag{2.4}$$

where j=1,2,..., J. Contrary to the Weibull model, the intervals may have different signs, that is, in a given time-interval the risk of failure may be positive but turn into negative in a subsequent interval. In fact, although the PWE is a parametric model, "a piecewise exponential hazard can approximate any shape of a non-parametric hazard" (Ibrahim et al., 2001). Thus, the PWE model is equivalent to the Cox model (to be discussed below), although, it is computationally simpler (Staplin et al., 2014). An important limitation of the PWE model is the ambiguity introduced by the need to define the number of intervals as well as the cut-off points (Ibrahim et al., 2001).

The PWE model that we estimate is based on the definition of intervals consisted with those reported in Table 2.1. However, we will ascertain whether the results are sensitive to the redefinition of other time intervals.

All the models reported above were estimated by maximum likelihood. Hence, the log-likelihood function to be maximized is given by eq. 2.5. where it is assumed that the non-informative censoring assumption holds:

$$\ln L = \sum_{i=1}^{n} \{c_i \ln [f(t_i)] + (1 - c_i) \ln [S(t_i)]\} \tag{2.5}$$

where n is the number of observations, c_i is 1 if the duration is completed, and 0 if censored. Completed observations contribute to the likelihood function by the density function f(.), and the weight of the censored ones are given by the survival function S(.). Notice that the density function can be written as follows:

$$f(t_i) = h(t_i) .S(t_i) \tag{2.6}$$

Thus, the density function corresponds to the product of the rate of occurrence of the event (surgery) at duration time t_i, and the probability of surviving the event at the same duration time.

We also take into account the Cox model proposed by Cox (1972):

$$h^{\text{COX}}(t) = h_0(t) \cdot \exp(\mathbf{X}\boldsymbol{\beta}) \tag{2.7}$$

where the baseline hazard function $h_0(t)$ is an unknown nonnegative function, and for that reason this model is called a semi-parametric model (Jones, 2000). The Cox model is estimated by the partial likelihood that may not be as efficient as the estimates of the maximum likelihood. However, it has the main advantage of not making assumptions (possibly inaccurate) for the baseline hazard function.

- As stated previously, estimation of the models is based on the non-informative censoring assumption meaning that it is assumed that the censoring times are independent of the failure times (conditional on values of variates) (O'Quigley, 2008; Sianni and Copas, 2005). Although treating informative censoring as non-informative may bias the estimates, it also recognises the difficulty on identifying informative censoring and testing its impact on results (Clark et al., 2003; Leung et al., 1997).

Therefore, since we cannot exclude the presence of informative censoring, we develop a sensitivity analysis to observe the impact of different survival times on estimates. We use the best and the worst scenarios approach, wherein, first we assume that censored data is non-informative (eq. 2.5 is applied), second, we consider an extreme relationship between the censored data and the hazard rate by assuming that all censored patients have surgery in the time they have cancelled (Clark et al., 2003).

If the estimates change considerably, it means that not correcting the likelihood function for the presence of informative censoring can have strong implications in the results. However, if the conclusions do not change, this means that even in the presence of informative censoring results are not particularly affected.

- Finally, to infer how the inclusion of cancellations impacts the results, we will also estimate the previous models (Weibull, Piecewise exponential model, and Cox) using only observations for patients submitted to surgery. Thus, for estimation of these models we will discard the data on cancellations. If there are differences to report between the two methods (i.e., with and without cancellations), this means that it is relevant to include cancellations in these kinds of studies.

2.4 Results

Table 2.4 reports the estimation of duration models (Weibull, Piecewise exponential and Cox)[4] where surgery is the event of interest and cancellation corresponds to the censored event.

The results indicate the Weibull, PWE and Cox models provide very similar estimates. Waiting times decrease to more severe priorities, with priority 4 having the shortest waiting times. Patients with cancer have shorter waiting times than patients not reported to have cancer.

In fact, the estimations show that prioritisation levels, as well as the cancer indicator,

[4]In the Cox model, the time is rounded to the unity (days) to make easier the convergence. Waiting times below one day are not included due to the inability of the model to handle values of 0. We estimated the Piecewise model with different time intervals. First, we include 5 intervals. Comparing with the base model (with 4 intervals) we added an interval for waiting times between 90 and 365 days and one interval for waiting times over 365 days. Then we include 6 categories: comparing with the base model we include the time intervals between 90 and 270 days, between 270 and 365 and other interval for times longer than 365 days. In both cases, the results are robust to show that the likelihood of surgery decreases over time.

Table 2.4: Estimation of the duration models

		Weibull	Piecewise exponential	Cox
Constant		0.2511***	-	-
Gender	Male	1.0245***	1.0267***	1.0255***
Cancer	Yes	1.4646***	1.5444***	1.6722***
Priority	2	2.2422***	2.3965***	2.4076***
	3	6.1818***	6.9288***	6.3812***
	4	11.6622***	12.7026***	8.3312***
Age	<15 years	0.9059***	0.9051***	0.9650***
	[15,30[	0.9581***	0.9565***	0.9696***
	[45,60[	0.9655***	0.9603***	0.9682***
	[60,75[	0.9482***	0.9409***	0.9509***
	>=75 years	0.9005***	0.8904***	0.8923***
ρ		0.7898	-	-
in_1		-	0.304***	-
in_2		-	0.120***	-
in_3		-	0.099***	-
in_4		-	0.086***	-
N		3,156,956	3,156,956	2,979,006
Wald		669,527.20***	5.59e+07***	1,763,284.17***
Log-pseudolikelihood		-5,407,195.6	-5,462,340	-
Partial log-likelihood		-	-	-34,816,220

$^{***}p < 0.01$

are the variables that most influence the waiting times for surgery as noted in the previous section. Men are more likely to be operated, and consequently, have shorter waiting times than women.

The age group from 30 to 45 years (reference group) is the one with the shortest waiting times. As age increases, the probability of surgery decreases, causing a rise in waiting times. Apparently, older patients face constraints in access to surgery.

The shape of the Weibull function shows a negative duration dependence $\rho < 1$ with a 95 % confidence interval between 0.7884 and 0.7912. Thus, the hazard function is monotonically decreasing indicating that the probability of surgery decreases over time. The fact that the confidence interval for ρ does not include the value 1 is an indication that the Exponential model is not a good fit for the data.

The PWE model shows a finding consistent with the Weibull model. The hazard rates across the four intervals ($in_1 : in_4$) indicate that the probability of surgery decreases over time. Like the Weibull model, the joint statistical significance of the four ranges considered in the PWE model shows that the exponential model should be rejected. The log-pseudolikelihoods of the Weibull and PWE model are also very identical.

Although the Cox model does not provide an estimate for the baseline hazard, it offers similar estimates for the impact of the covariates with the exception of the coefficient for priority 4. That difference may be possibly explained by the fact that the model does not include waiting times below one day, and therefore excludes patients with more severe priorities.

- The Appendix shows the extreme sensitivity analysis to observe the effect that informative censoring has on results. As expressed in the previous section, in the worst scenario, all censored patients are estimated as if they had been operated at the time of cancellation.

The estimates show that there are no differences to report between the best scenario (Table 2.4) and the worst scenario (Appendix – Table A2.1). Thus, we are lead to conclude that informative censoring does not seem to have an impact on the reported conclusions.

Table 2.5: Estimation of the duration models for operated episodes

		Weibull	Piecewise exponential	Cox
Constant		0.3152***	-	-
Gender	Male	1.0365***	1.0396***	1.0412***
Cancer	Yes	1.3533***	1.4202***	1.5621***
Priority	2	2.2642***	2.4498***	2.5099***
	3	6.7989***	7.4902***	7.2844***
	4	15.877***	16.6104***	12.4443***
Age	<15 years	0.8603***	0.8572***	0.9252***
	[15,30[	0.9628***	0.9615***	0.9766***
	[45,60[	0.9650***	0.9594***	0.9611***
	[60,75[	0.9716***	0.9656***	0.9664***
	>=75 years	0.9986	0.9928**	0.9888***
ρ		0.8763	-	-
in_1		-	0.4561***	-
in_2		-	0.2152***	-
in_3		-	0.1989***	-
in_4		-	0.2177***	-
N		2,690,554	2,690,533	2,527,768
Wald		848,965.25***	5.39e+07***	1,588,936.14***
Log-pseudolikelihood		-4,650,420.4	-4,654,880.3	-
Partial log-likelihood		-	-	-34,076,100

$^{***}p < 0.01$, $^{**}p < 0.05$

- Table 2.5 displays the estimates of waiting times to scheduled surgery if we did not include the cancellations in the estimations.

The findings in Table 2.5 are identical for the three estimation methods. Once more $\rho < 1$ showing a 95 % confidence interval between 0.8745 and 0.8781. The PWE model provides the same conclusion, leading us to state that the exponential model should not be applied.

It is also noteworthy that the estimates of the coefficients for gender and priority are larger suggesting that the impact of these variables may be overestimated. More flagrant is the case for priority 4 with estimates that range between 36 to 50% higher.

On the other hand, the estimates of the coefficient for the cancer variable is undervalued between 6.6 to 8%. That is, everything else constant, patients with cancer would have estimated longer waiting times for surgery than those displayed by the models that focused exclusively on the operated episodes.

We also emphasise the coefficients of the variable age. Although the age group from 30 to 45 is again the one with shortest waiting times (in all the three models), from the age ranged 45 to 60 the hazards start to increase (decrease in waiting times), contrary to the results expressed in Table 2.4. In the Weibull model, there are no differences to report between the group over 75 years and the one between 30 and 45 years.

Thus, the estimates show that drawing conclusions about those factors that impact on waiting times based only on the subsample of patients submitted to surgery would exclude valuable information and might not correctly inform decision makers.

2.5 Reasons for cancellation

There are many different reasons why surgeries are cancelled. Given that we have information on the reasons for cancellation we also aim to investigate if there are factors that are associated with the different types of cancellation. For simplicity, we group the reasons for cancellation into six homogeneous groups. The reasons in each group are similar and therefore, should be explained by the same factors. Information on motivations for cancellation was also provided by ACSS.

Table 2.6 reports the distribution of cancellations across the six groups. Reason 1 corresponds to patient "withdrawal", whose decision is up to the patient, after being contacted for a surgical appointment. It also includes "non-attendance (three times) with plausible reasons", "non-attendance with no plausible reasons", or "non-activation of the surgery voucher within three months" (after the hospital has issued a surgery voucher because the waiting times for patient's transfer have been reached). The date of cancellation corresponded to the date when the hospital took formal notice of the event.

Reason 2 refers to cancellation due to clinical reasons. It includes "patient without surgical indication", "patient without operative conditions due to clinical reasons" and "surgical proposal not appropriate to the clinical condition". The date of cancellation

Table 2.6: Reasons for cancellation

Reason	Cancellation
1	176,461 (37.83%)
2	85,023 (18.23%)
3	43,759 (9.38%)
4	37,547 (8.05%)
5	9,837 (2.11%)
6	113,811 (24.40%)
TOTAL	466,438 (100%)

was the date when the hospital identified the situation.

Reason 3 corresponds to cancellations that refer to surgical episodes that were actually carried out. It includes records reporting "patient urgently operated in the hospital of origin", that is, the patient was operated during a worsening of his clinical situation in the emergency department of the hospital he was registered. Reason 3 also includes the "patients operated on a scheduled basis in the hospital of origin". It occurs when a hospital to which surgery has been transferred finds that surgery has already been performed at the hospital of origin. Finally, reason 3 also covers "patient operated in another hospital" within or outside the SIGIC. For the first two cases, the date of cancellation refers to the time the surgery was performed, and the latter corresponds to the date when the hospital of origin took formal notice of the operation.

Reason 4 is concerned with the "transfer of responsibility" of total disease treatment to a new intra/inter-hospital service or functional unit. The cancellation date refers to the validation date of the surgical proposal in the new service or functional unit.

Reason 5 corresponds to patients' "death" where the date of cancellation corresponds to the date of death. Reason 6 refers to the remaining motivations.[5] For further information on cancellations check the following reports ACSS (2011a), ACSS (2011b), ACSS (2011c) and ACSS (2011d).

Table 2.6 shows that withdrawal is the most common reason for cancellation (37.83%), followed by cancellations due to clinical reasons (18.23%). The third reason reveals that 9.39% of the patients were previously operated.

To observe how patient characteristics and clinical prioritisation have influenced

[5]We excluded reason 6 from the econometric analysis because it covers very different motivations.

the different types of cancellation, we estimated a multinomial logit with the following specification.

$$\frac{P(Y=m)}{P(Y=1)} = \exp(\mathbf{X}'\boldsymbol{\beta}_m) \tag{2.8}$$

where Y is a categorical variable and the subscript "m" corresponds to the reasons for cancellation that go from 1 to 5. In the estimation withdrawal (Reason 1) will be the reference category and thus the model is parametrised accordingly.

In line with the previous models, we analyse the effect on the different types of cancellation, of the following variables: gender, age, prioritisation and oncological indicator. A higher risk of a given kind of cancellation by a particular group of patients may indicate a concrete barrier in access. For instance, if $\beta_{\text{male }21} > 1$ it means that men have a higher risk of cancellation by motivation 2 than by withdrawal.

Also, observe that patients with more severe priorities or patients reported with cancer may be less exposed to cancellations in general, but they may be associated with cancellations of a more acute nature, such as death.

We also control for hospital, procedure, municipality of residence, year.[6] Appendix – Table A2.2 shows the frequency of the most relevant variables by type of cancellation. The estimation of the multinomial logit and predictive margins are in Appendix - Table A2.3 and Table A2.4, respectively. Table 2.7 shows the average marginal effects where the coefficients correspond to discrete changes from the base level.

The results show that, everything else constant, compared to women men have an average probability of cancellation by death 1.45 percentage points (pp) higher, which may indicate that men tend to be in more serious health condition before surgery. On the other hand, Table 2.7 also reports that men have on average a probability of withdrawal which is 1.91 pp lower than women.

Having the more severe priority increases the average probability of having surgery previously, by 25 pp (priority 4 compared with priority 1). On the contrary, it decreases the probability of withdrawal by 38 pp. This result suggests that withdrawals are more related to less severe clinical conditions.

[6] The variable "speciality" was excluded from the multinomial logit model because it prevented the estimation of standard deviations for predicted effects and average marginal effects.

Table 2.7: Average marginal effects - eq. 2.8

		Y=1 Withdrawal	Y=2 Clinical reasons	Y=3 Patients already operated	Y=4 Transfer	Y=5 Death
Gender	Male	-0.0191***	0.0049***	0.0021*	-0.0024***	0.0145***
Cancer	Yes	-0.0659***	0.0231***	-0.0025	0.0333***	0.0119***
Priority	2	-0.1135***	0.0312***	0.0639***	0.0147***	0.0037***
	3	-0.2480***	0.0535***	0.1483***	0.0386***	0.0076***
	4	-0.3780***	0.0316***	0.2503***	0.0886***	0.0025
Age-group	<15 years	-0.1211***	0.0959***	-0.0041	0.0323***	-0.0041***
	[15,30[	0.0114***	0.0012	-0.0074***	-0.0011	-0.0042***
	[45,60[	-0.0227***	0.0218***	-0.0068***	0.0003	0.0074***
	[60,75[	-0.0343***	0.0380***	-0.0148***	-0.0092***	0.0203***
	>=75 years	0.0111***	0.0186***	-0.0426***	-0.0338***	0.0467***

$^{***}p < 0.01$, $^{*}p < 0.10$

It is also shown that patients reported with cancer raises the probability of cancellation by transfer of responsibility by 3 pp, followed by deterioration of the clinical condition with an increase of 2 pp. With the opposite sign, we observed that the oncologic indicator contributed to a decrease in the probability of withdrawal of 7 pp.

Older patients increase the probability of death by 5 pp compared to the omitted category (patients aged 30 to 45). This result was expected since age increases exposure to this kind of cancellation. On the other hand, younger patients increase the probability of waiting list exit by clinical reasons by 10 pp. This result can be explained by the fact that for some surgical procedures, it is required a stable pathology and minimum ages as well.

A more detailed look at the data allowed us to realise that 6.68% of patients who had surgery did not have their priority met. In contrast, priority non-compliance among patients who cancelled surgery was 22.29%. This suggests that some cancellations may be due to the fact that some priority targets are not being met.

To understand if priority non-compliance was associated with type of cancellation we proceeded in the following fashion.

First, we created a variable "priority exceeded" that takes 1 if there is no compliance with the maximum times and 0 otherwise. For this variable, we consider the maximum times (for each priority) as shown in Table 2.2. We then estimated a logit model as eq. 2.9 to obtain for each patient an estimate of the probability that each patient had his/her priority exceeded (Pr priority exceeded):

$$\frac{P(priorityexceeded = 1)}{1 - P(priorityexceeded = 1)} = \exp(\mathbf{X}'\boldsymbol{\beta}) \tag{2.9}$$

where the priority exceeded is the dependent variable, and the independent variables are the same as previous models: gender, age, priority, cancer, year, hospital, municipality, procedure code. In this specification we also included the speciality.

After estimating the logit model we computed the variable "Pr priority exceeded" (expressed in decimal values) which we added as a regressor to the multinomial logit model with five categories:

$$\frac{P(Y = m)}{P(Y = 1)} = \exp(\beta_{1,m/1} + \beta_{2,m/1} * \text{ Pr } \text{ priorityexceeded }) \tag{2.10}$$

The estimation of the multinomial logit model is shown in the Appendix - Table A2.5 and the predictive margins are in Appendix - Figure A2.1. Table 2.8 shows the average marginal effects for this variable at mean values.

Table 2.8: Average marginal effects- eq. 2.10

	Y=1 Withdrawal	Y=2 Clinical reasons	Y=3 Patients already operated	Y=4 Transfer	Y=5 Death
Pr_priority exceeded	0.0155***	0.0264***	0.0651***	-0.1442***	0.0373***

$^{***}p < 0.01$

The coefficient estimates indicate that increases in the probability of priority non-compliance have a larger impact on the probability of having surgery previously and on cancellation by death. On the other hand, the results show that priority non-compliance decreases the risk of cancellation by transfer of responsibility, suggesting that this procedure still occurs within the maximum times of each priority.

2.6 Discussion

This paper argues that estimating survival models with episodes of surgery along with cancellations should be the appropriate way to evaluate the impact of factors that impact on waiting times for surgery.

We did so by testing different survival models. It should be noted that age was the only variable for which the models provided different conclusions. That is, if we did not include cancellations, we would conclude that older patients tend to have shorter waiting times. We would neglect, for instance, that older patients cancel with longer waiting times compared to other age groups. The other variables have no different estimates in both methods because the waiting times' pattern for surgery and cancellation is the same.

Our study also allowed us to reach some meaningful findings concerning equity in access to scheduled surgery in the Portuguese NHS. Patients with cancer have shorter waiting times, although we also observed that those patients have an increased risk of cancellation due to transfer of responsibility or deterioration of the clinical condition.

Thus, patients with cancer are more likely to be transferred, which may reveal hospital coordination to improve access to these patients. Unfortunately, our databases do not allow us to track the patients to the new hospitals or functional units to assess the total waiting times. The second result shows, however, that these patients had their clinical condition deteriorated, which may be related to cancer, but also because they may not receive timely treatment specific to their clinical condition.

The results also indicate that men have a higher probability of being submitted to surgery. This finding is in line with Cima et al. (2018), Johar et al. (2013), Moscelli et al. (2018). At first sight, this result could indicate discriminatory conduct, because even controlling for a set of covariates, the results pointed out that men had shorter waiting times for surgery than women. The result is even more surprising when we look at the types of cancellation since men have an increased probability of cancellation by death. The fact that men wait less time for surgery or have a higher risk of death comparing with women suggests they enter on the waiting list displaying worse clinical conditions, such as a higher number of comorbidities. However, we do not have information regarding the number of comorbidities in our database.

Regarding the variable "age" the results show that the waiting times start to increase from the age of 45. Patients aged between 30 and 45 years are associated with shorter waiting times. A similar conclusion was reached by Johar et al. (2013) regarding the impact of age on waiting times, that is, older patients have longer waiting times. Likewise, Cookson et al. (2013) showed that age is a barrier to access to surgery when they found that age above 50 years was relevant in explaining cancellations, and that the effect got stronger as age increased.

Furthermore, there are several points to mention regarding the Portuguese prioritisation system. First, higher priorities have shorter waiting times when compared to less severe priorities. However, concerning the cancelled episodes, we observed that patients with more severe priorities have a higher risk of cancelling because they have been operated before, or because they have been transferred. This fact implies that those patients presented such severity that they needed to have surgery in other circumstances and that hospitals of origin were unable to respond to such severity.

Second, failure to meet the waiting times for each priority is also a relevant factor in explaining waiting list exit. The most relevant case is the cancellation for having surgery previously and cancellation by death. Thus, although prioritisation seems to work, there is room for improvement in the sense that there must be an increased effort by the NHS to not exceed the maximum times for each priority.

2.7 Conclusion

This study analyses equity in access to surgery and the impact of patient's prioritisation, using all available information, which includes surgical procedures along with cancellations. We use all patient-level administrative data of the Portuguese NHS between 2011 and 2015, and the results showed that a study focused only on surgical episodes could be somewhat restrictive to reach comprehensive findings.

The results also identified that the prioritisation seems to work correctly since patients with higher priorities have shorter waiting times. However, there is still a need for additional efforts aimed at reducing some inequalities and prioritisation patterns that have been found in the various types of cancellation.

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Appendix

Table A2.1: Sensitivity analysis with the worst scenario – Informative censoring

		Weibull	Piecewise exponential	Cox
Constant		0.2135***	-	-
Gender	Male	1.0298***	1.0324***	1.0324***
Cancer	Yes	1.4354***	1.5277***	1.6524***
Priority	2	2.1847***	2.3595***	2.3578***
	3	5.9637***	6.5997***	6.1212***
	4	11.4302***	12.0688***	8.3877***
Age	<15 years	0.8916***	0.8910***	0.9474***
	[15,30[	0.9626***	0.9610***	0.9729***
	[45,60[	0.9646***	0.9580***	0.9649***
	[60,75[	0.9597***	0.9502***	0.9607***
	>=75 years	0.9496***	0.9355***	0.9401***
ρ		0.8240	-	-
in_1		-	0.2818***	-
in_2		-	0.1092***	-
in_3		-	0.0920***	-
in_4		-	0.0960***	-
N		3,156,956	3,156,933	2,979,006
Wald		666,407.50***	6.80e+07***	2,063,699.18***
Log-pseudolikelihood		-5,638,551.5	-5,674,005.1	-
Partial log-likelihood		-	-	-40,725,733

$^{***}p < 0.01$, The 95% confidence interval for ρ is: [0.8225, 0.8254].

Table A2.2: Descriptive statistics by type of cancellation

Motivation	Y=1 Withdrawal	Y=2 Clinical reasons	Y=3 Patients already operated	Y=4 Transfer	Y=5 Death
Gender					
Female	103,910 (58.89%)	48,001 (56.46%)	24,067 (55%)	24,138 (64.29%)	3,979 (40.45%)
Male	72,551 (41.11%)	37,022 (43.54%)	19,692 (45%)	13,409 (35.71%)	5,858 (59.55%)
Priority					
1	163,368 (92.58%)	69,669 (81.94%)	32,238 (73.67%)	32,278 (85.97%)	7,132 (72.50%)
2	11,391 (6.46%)	11,617 (13.66%)	7,109 (16.25%)	3,486 (9.28%)	1,872 (19,03%)
3	1,298 (0.74%)	2,500 (2.94%)	2,530 (5.78%)	787 (2.10%)	554 (5.63%)
4	404 (0.23%)	1,237 (1.45%)	1,882 (4.30%)	996 (2.65%)	279 (2.84%)
Cancer					
Yes	4,207 (2.38%)	5,684 (6.69%)	2,490 (5.69%)	1,985 (2.89%)	1,088 (11.06%)
No	172,254 (97.62%)	79,339 (93.31%)	41,269 (94.31%)	36,462 (97.11%)	8,749 (88.94%)
Age groups					
<15 years	7,255 (4.11%)	5,492 (6.46%)	2,743 (6.27%)	1,919 (5.11%)	38 (0.39%)
[15,30[	14,669 (8.31%)	5,569 (6.55%)	3,407 (7.79%)	2,915 (7.76%)	42 (0.43%)
[30,45[	28,283 (16.03%)	11,569 (13.61%)	7,862 (17.97%)	7,286 (19.41%)	239 (2.43%)
[45,60[	40,566 (22.99%)	18,603 (21.88%)	10,158 (23.21%)	10,378 (27.64%)	901 (9.16%)
[60,75[	46,833 (26.54%)	24,443 (28.75%)	11,704 (26.75%)	10,137 (27.00%)	2,719 (27.64%)
>=75 years	38,855 (22.02%)	19,347 (22.76%)	7,885 (18.02%)	4,912 (10.08%)	5,898 (59.96%)
Priority exceed					
Yes	40,771 (23.10%)	21,906 (25.76%)	8,716 (19.92%)	3,806 (10.14%)	2,753 (27.99%)
No	135,690 (76.90%)	63,117 (74.24%)	35,043 (80.08%)	33,741 (89.86%)	7,084 (72.01%)

Table A2.3: Estimation of the multinomial logit - eq. 2.8

		Y=2 vs. Y=1	Y=3 vs. Y=1	Y=4 vs. Y=1	Y=5 vs. Y=1
constant		0.2289***	0.1339***	0.0009***	0.0035***
Gender	Male	1.0752***	1.0757***	1.0027	1.8413***
Cancer	Yes	1.3002***	1.1844***	1.9640***	1.7586***
Priority	2	1.5269***	2.3328***	1.7303***	1.5505***
	3	2.6158***	6.0391***	3.9728***	2.8113***
	4	4.5694***	18.2842***	14.7887***	4.6676***
Age-group	<15 years	2.0168***	1.3657***	2.1809***	0.5137***
	[15,30[	0.9771	0.9075***	0.9539	0.3316***
	[45,60[	1.1697***	1.0012	1.0539**	2.3014***
	[60,75[	1.2951***	0.9611**	0.9182***	4.6717***
	>=75years	1.0722***	0.6362***	0.5099***	8.5226***
Log likelihood		-348654.54			
Observations		352,546			
LR		209809.54***			

$^{***}p < 0.01$, $^{**}p < 0.05$

Table A2.4: Predictive margins - eq. 2.8

	Y=1 Withdrawal	Y=2 Clinical reasons	Y=3 Patients already operated	Y=4 Transfer	Y=5 Death
Gender					
Male	0.4899***	0.2442***	0.1253***	0.1050***	0.0357***
Female	0.5090***	0.2393***	0.1232***	0.1074***	0.0212***
Cancer					
Yes	0.4371***	0.2634***	0.1219***	0.1388***	0.0389***
No	0.5029***	0.2403***	0.1243***	0.1054***	0.0270***
Priority					
1	0.5199***	0.2387***	0.1104***	0.1034***	0.0277***
2	0.4064***	0.2699***	0.1743***	0.1181***	0.0314***
3	0.2719***	0.2922***	0.2587***	0.1420***	0.0353***
4	0.1469***	0.2703***	0.3607***	0.1920***	0.0301***
Age-group					
<15 years	0.3996***	0.3140***	0.1368***	0.1472***	0.0024***
[15,30[	0.5322***	0.2193***	0.1334***	0.1129***	0.0022***
[30,45[	0.5207***	0.2181***	0.1408***	0.1140***	0.0064***
[45,60[	0.4980***	0.2399***	0.1340***	0.1143***	0.0138***
[60,75[	0.4864***	0.2561***	0.1260***	0.1047***	0.0267***
>=75 years	0.5319***	0.2366***	0.0982***	0.0802***	0.0531***

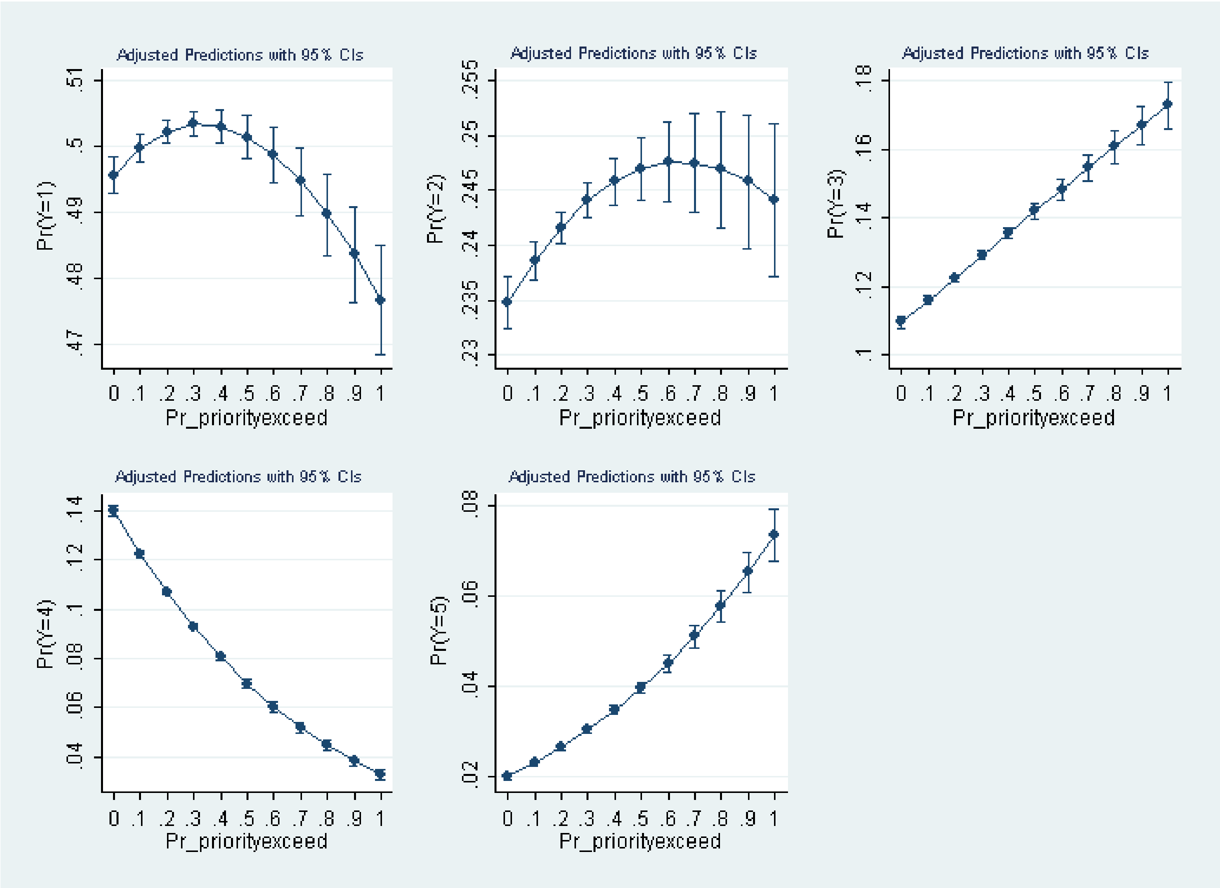
$^{***}p < 0.01$

Table A2.5: Estimation of the multinomial logit - eq. 2.10

	Y=2 vs. Y=1	Y=3 vs. Y=1	Y=4 vs. Y=1	Y=5 vs. Y=1
Pr_priority exceeded	1.0813***	1.6417***	0.2435***	3.7990***
constant	0.4736***	0.2209***	0.2823***	0.0406***
Log likelihood	-452000.59			
Observations	352,397			
LR	2529.90***			

$^{***}p < 0.01$

Figure A2.1: Predictive margins - eq. 2.10



Chapter 3

Waiting times for scheduled surgery in the Portuguese NHS: a spatial econometric analysis

Abstract

In this study, we analyse the spatial interactions among hospitals in the Portuguese National Health Service regarding the access to scheduled surgery. Since the waiting times have been increasing in the last years, identifying possible strategic interactions is essential in designing more effective policies in access to surgery. Using data that comprises information for Portuguese NHS hospitals from 2013 and 2015, we estimate two hospital-specific indexes for waiting times and cancellations (as proxies for hospital quality), derived from patient-data. Then, we identify a spatial pattern among hospitals by employing spatial panel models, namely, the spatial lag model and the spatial Durbin model. The results are robust in showing a spatial dependence in waiting times and in the probability of cancellation as well. Thus, the results indicate there is evidence of spillovers in waiting lists that should be used for more efficient management of access to surgery and that identify the hospitals' features that contribute the most to these findings.

Keywords: scheduled surgery, access, spatial models, Portugal

JEL Classification: *I14*, *C01*

3.1 Introduction

The extensive waiting lists for both appointments and scheduled surgeries are a persistent problem in access to health in public health systems (Siciliani et al., 2013). This fact contributes to higher waiting times, which besides harming the patient's clinical condition (Koopmanschap et al., 2005), may also impact on public perception regarding the health care systems (Clery, 2012; Siciliani and Hurst, 2005). The same concern applies to Portugal, wherein the waiting times for surgery have gradually increased in recent years (Cima et al., 2018), with the cancellation rate remaining about 14% in 2015.

Identifying public health policies aimed at controlling waiting times is then crucial to ensure better management of the waiting list and improved access to surgical treatment (shorter waiting times) (Siciliani et al., 2013).

The competition among hospitals is a standard policy to pressure hospital' managers to guide their strategy to increase both efficiency and productivity (Bloom et al., 2015; Cooper and McGuire, 2014); in other words, "to give people what they want in the least costly way possible" (Barros et al., 2016). Despite the pressures for cost containment and search for more efficient mechanisms, the potential negative impact of competition on quality and access to health care may not be ignored (Barros et al., 2016; Cookson et al., 2013).

Thus, a key question in this study is to analyse whether there is evidence of competition/spillovers in the Portuguese NHS, and how it impacts on surgery waiting times and cancellations. In the period we are analysing, there was no free patient choice in the Portuguese NHS (at least, not formally). It means that patients were refereed and treated based on their area of residence until the year 2016 (Diário da República, 2016; Simões et al., 2017).

However, there are other interactions among hospitals, such as competition for health staff, presence of peer effects among physicians or hospital managers (Barros, 2017; Lisi et al., 2017), or hospitals' agreements (e.g., with Misericordia's hospitals) which can impact waiting times.

Thus, rather than examining the impact of competition on waiting times and using a common market concentration measure, like perhaps the Herfindahl-Hirschman index (HHI), our study seeks to find strategic interactions among hospitals and potential spillovers at the surgery level that decision-makers may use to disseminate policies and best practices.

Our study uses data for Portuguese NHS hospitals from 2013 to 2015. First, we estimate two hospital-specific indexes for waiting times and cancellations, obtained from patient data, as a proxy for hospital quality. Our approach removes all factors that may influence waiting times and cancellations (e.g., the severity of the clinical condition or patients' characteristics) that are not directly attributed to hospitals.

Then, we estimate spatial panel models to observe endogenous or exogenous spatial dependence patterns between hospitals. We take into consideration factors such as the hospitals' organisational structure, dimension, or teaching status, and we are able to find the hospitals' features that explain the access to surgery.

We are aware that hospitals may not compete deliberately in terms of waiting times or cancellations. However, these indicators are explained by internal decisions and by hospitals' effort to reach their specific goals.

The rest of this paper is organised as follows. In section 2 we provide a brief review of the relevant literature. Section 3 describes the methodology used in this paper. Our results are in section 4. Section 5 provides an analysis of the spatial dependence with cancellations. Section 6 discusses, and Section 7 concludes.

3.2 Background

Competition in health markets such as among hospitals is well documented in the literature (Dranove and Satterthwaite, 2000; Gaynor and Town, 2011; Gaynor and Vogt, 2000; Pauly, 2004). Although hospitals may compete via price or quality, in cases where prices are set administratively rather than determined by the market, as in National Health Systems, competition is via quality (Gaynor and Town, 2011; Pauly, 2004). Gaynor and Town (2011) noted that although "hospitals may not directly choose a quality level" hospitals can "choose overall effort, or slack, based on the incentive they face".

The literature tends to the point that competition has a positive impact on hospital quality in markets where prices are defined administratively. See, for instance, the studies of Kessler and McClellan (2000) and Kessler and Geppert (2005) concerning the Medicare in the USA, and Gaynor et al. (2013), Cooper et al. (2011) and Bloom et al. (2015) for the UK's case. A common approach in this kind of literature is to include a measure of market concentration, usually the HHI [1] , and observe how the concentration index affects the service's quality. The last is often measured by patient mortality for patients with myocardial infarction (Brekke et al., 2014; Gaynor and Town, 2011).

However, a literature has emerged that seeks to analyse the interaction processes between individuals or economic agents, and which recognises the importance of spatial dependence in health economic studies (Moscone and Tosetti, 2014; Tosetti et al., 2018). In fact, competition between healthcare providers has benefited from the application of spatial econometric models, namely from spatial lag models. This kind of models allows studying the impact of competition on prices and quality by estimating hospital reaction functions (Gravelle et al., 2014; Longo et al., 2017; Mobley, 2003; Mobley et al., 2009).

Mobley (2003) estimates prices response functions in California hospital market to observe how the spatial proximity of the rivals and the spillovers effects impacted on prices. The results reveal that the slope of the reaction function was positive and did not change significantly over time. Using the same data, Mobley et al. (2009) note the relevance of estimating spatial models in analysing competition in the hospital's market. They recognised some problems when OLS is applied, such as inaccurate standard errors.

Gravelle et al. (2014) follow a similar approach by employing hospital response functions, however investigating the effect of competition on quality. The authors studied the competition between health care providers in the UK by investigating whether a hospital's quality is affected by the quality of rival's hospitals. The authors use sixteen quality measures, seven of which are positively related to the quality of neighbouring hospitals. They remarked that a spillover at the quality level could contribute to an

[1] HHI index corresponds to the sum of squared market shares. Larger hospitals have a higher weight in the index.

improvement in the quality of a hospital.

Longo et al. (2017) extend the analysis and examine whether English NHS hospitals respond in terms of quality and efficiency. Employing spatial cross-sectional and spatial fixed and random-effects panel data models, the authors use eight quality measures and six efficiency indicators. They found there is no evidence of hospital spillovers, except for hospital's overall mortality which is positively correlated with that of its rivals.

The impact of hospital competition on surgery waiting times has already been addressed by Brekke et al. (2008). The authors use a Salop-theoretical model and conclude that competition among hospitals reduces waiting times if the free choice is not sufficiently relevant in the total number of patients. Otherwise, competition could lead to increased waiting times to avoid unprofitable patients.

Thus, our study makes a contribution to this research field by empirically analysing the strategic spatial interactions in scheduled surgery in Portugal NHS. Since free patient's choice is not particularly relevant in our study, we observe whether our results are consistent with the Brekke et al. (2008)'s model. Note that in a competitive environment, quality is a strategic complement, that is, a hospital will respond to an improvement in the quality of neighbouring hospitals while raising the quality of its own services (Longo et al., 2017).

It is also worth mentioning that, in Portugal, there are different types of hospital ownership/management, as well as hospital organisation models, which will be taken into account in the spatial models and that we present next.

The first group includes Hospitals PPP (Public-Private partnerships) that refer to the private sector's participation in the design, construction, financing or administration of NHS hospitals (see Barros and Martinez-Giralt, 2009, for more information on contractual PPP's design for hospitals in Portugal). In fact, this management model in which the public authority contracts with the private sector the construction and management of hospitals has been applied in several countries with national health services (McKee et al., 2006), to generate savings in public resources' use with risk sharing between public and private sector. Despite the fact that investment and management are private, access to medical care remains the same as this is available in other public hospitals (ACSS, 2016; Diário da República, 2012).

Misericórdias' hospitals (Holy House of Mercy) also concern a type of hospital ownership. They are part of a private nonprofit organisation (Santa Casa da Misericordia) inspired by catholic faith (Almeida, 2017), which integrates the Portuguese third sector organisations (i.e., social sector). Thus, it occupies a privileged position covering population that the private sector (as a profit-maximiser) can't, and to whose health demand governments can't respond.

Even though surgeries are primarily performed in public hospitals, they can also be carried out in Misericordia' hospitals through cooperation agreements with their geographical area's Regional Health Administration (Diário da República, 2004). Finally, there is the public sector management in which both public administrative sector hospitals and public enterprise hospitals are included.

The hospital organisation models include IPOs (Portuguese Oncology Institutes) that provide highly specialised and differentiated healthcare in cancer treatment and research (Brás et al., 2017); CHs (Hospital Centers) that result from a horizontal merger of hospital units and seek efficiency gains (e.g., economies of scale) (ERS, 2012a); ULSs (Local Health Units) that are structures of vertical integration that include primary care, hospital care and integrated continuous care and that are responsible for the health status of a given population (ERS, 2015; OECD, 2015). Hospital units that do not fit into the types mentioned above will be called "hospital unit".

3.3 Data and Methodology

3.3.1 Theoretical Background

This study examines whether there are strategic interactions among hospitals in waiting times in access to scheduled surgery in the Portuguese NHS. To this end, we extend the theoretical model with regulated prices proposed by Gravelle et al. (2014). The demand function of hospital "i" is given by:

$$D_i = D\left(q_i, q_{-i}, \gamma_i\right) \tag{3.1}$$

in which q_i corresponds to the quality of hospital "i" and q_{-i} refers to the rivals' quality. The quality of hospital "i" is expected to increase with its own demand. On the other hand, when the quality of the neighbouring hospitals improves, the demand for hospital "i" is expected to decrease. γ_i corresponds to a vector of exogenous variables that also affect hospital demand.

The utility function of hospital "i" is as follows:

$$U_i = p \cdot D_i\left(q_i, q_{-i}, \gamma_i\right) - C\left(D_i, q_i, \mu_i\right) \tag{3.2}$$

where p is the fixed price that the hospital receives from a third-payer. $C(.)$ is the cost function of hospital "i" that increases with demand and quality, while μ_i corresponds to exogenous factors that impact on hospital costs. Maximizing the utility function with respect to q_i, and solving for q_i, we get the reaction function of hospital "i":

$$q_i^R = q_i^R\left(q_{-i}; \gamma_i; \mu_i\right) \tag{3.3}$$

Thus, hospital reaction functions depend on the neighbours' quality and on exogenous variables that are assumed to impact the hospital's demand and costs.

Our empirical approach is based on the above model where we use a hospital weighted waiting time index (to be explained in the next section) as a proxy for quality. Our measure of hospital quality, q^w, is purged of all patient related characteristics that influence the demand of the hospital. Therefore, the hospital reaction can now be expressed as:

$$q_i^{Rw} = q_i^{Rw}\left(q_{-i}^w; \mu_i\right) \tag{3.4}$$

where we have replaced q_i by our index of hospital quality, q^w. Given the nature of q^w, we expect the dependence degree between q_{-i}^w and q_i^w to be affected only by hospital characteristics (e.g., dimension, hospitals' organisational structure) and consequently we now exclude γ_i from the argument of the reaction function.

Thus, the empirical analysis to be developed below comprises two parts. First, using patient-level data, we run a linear regression model with high-dimensional fixed effects to create our measure of hospital quality (q^w). The measure can be interpreted as the average waiting time per hospital which is adjusted for patient demographic characteristics as well as other characteristics that capture the nature and complexity of the treatment. Otherwise, the waiting times might not be directly attributed to specificities of the hospital, but to the mix of patients who might have specific pathologies that would guarantee lower/higher waiting times. This concern is addressed, for example, by Brekke et al. (2014) that note the importance of allowing quality to be affected by patient characteristics in competition and quality studies. In the second step we use our measure of hospital quality as a dependent variable in a panel regression that accounts for possible spatial dependence. The analysis is implemented using hospital-level data and, in accordance with the theoretical model presented above, we control for a variety of hospital characteristics.

3.3.2 Hospital-waiting time index

In this section we describe in more detail how we built the hospital waiting time index which consists of an adjusted average of waiting times. The measure only considers patients that were submitted to surgery.

For this exercise we analysed the administrative data for access to surgery that were obtained from SIGIC for a three year period comprising the years of 2013 through 2015[2]. The data is at the patient-level and provides different types of information with respect to the patient and type of surgical procedure. Table 3.1 reports descriptive statistics for some of the variables.

To obtain the waiting time index we estimated the following econometric specification:

$$\mathbf{Y} = \boldsymbol{\beta}^{\text{index}}\, \mathbf{Hospital} * \mathbf{Year} + \mathbf{X}\boldsymbol{\beta}^{\text{COV}} + \boldsymbol{\varepsilon} \tag{3.5}$$

where $\mathbf{Y}$ corresponds to a vector of patients' waiting times (in logs). [3] Our measure of hospital quality is given by $\boldsymbol{\beta}^{\text{index}}$ – the coefficients of the hospital × year interaction.

[2]We included the period from 2013 to 2015 for the sake of comparability. See that Hospital of Beatriz Ângelo - Loures started operating in the first months of 2012, with a reduced number of surgeries compared to subsequent years.

[3]Waiting times that equal zero have been replaced by half of the minimum waiting times when excluding zeros. They represented 0.1364% of the total number of observations.

Table 3.1: Descriptive statistics of surgery's waiting times – patient data

		Waiting times				
Variable	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
Gender						
Female	936,521 (57.16%)	77.14	41.72	101.45	0	3707.35
Male	701,843 (42.84%)	73.16	38.66	95.60	0	3577.70
Cancer						
Yes	135,162 (8.25%)	26.57	20.38	29.30	0	881.53
No	1,503,202 (91.75%)	79.83	45.35	101.85	0	3707.35
Priority						
1	1,249,863 (76.29%)	92.38	60.56	105.92	0	3707.35
2	268,818 (16.41%)	27.94	18.58	41.15	0	2582.62
3	70,581 (4.31%)	7.18	2.81	18.38	0	2121.60
4	49,102 (3.00%)	2.26	1.35	7.19	0	429.84
Age groups						
<15 years	95,801 (5.85%)	93.00	67.37	91.47	0	1203.37
[15,30[	107,743 (6.58%)	81.79	49.52	99.16	0	2271.35
[30,45[	236,659 (14.44%)	76.56	43.63	99.41	0	3707.35
[45,60[	373,547 (22.80%)	79.19	43.46	105.38	0	2620.34
[60,75[	473,225 (28.88%)	74.77	38.36	100.81	0	3577.70
>=75 years	351,389 (21.45%)	64.84	30.40	89.65	0	3446.69

Quality is expected to vary over the years due to variations in hospitals available resources and possible changes in management or management practices. **X** is a vector of covariates that controls for several sources of heterogeneity at the level of the patient. More specifically, we control for the speciality and surgical procedure because they are related to specific treatment complexities and different resources availabilities. This fact can naturally contribute to distinct waiting times between hospitals. We also add the priority of the patient's clinical condition and the cancer indicator as proxies for severity. We understand that they may be relevant in explaining variations in waiting times between hospitals. In fact, hospitals that are more exposed to patients with more severe priorities are expected to have shorter waiting times to meet the maximum time associated with those priority levels. Finally, we also include individual specific variables such as age, gender, or place of residence that impact on patient length of stay. If not accounted for, different mixes of patients across hospitals could be misperceived as differences in quality as proxied by length of stay.

By removing all effects that are expected to impact on waiting times and that are not directly explained by hospital specificities, we can conclude that hospitals with

Table 3.2: Summary statistics for waiting time index by hospital-specific variables

Variables	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
Organisational structure						
IPO	9 (5.08)	0.1539	0.4476	0.4763	-0.5636	0.5640
Hospital	29 (16.38)	0.0147	0.1449	0.3926	-0.8644	0.5952
CH	63 (35.59)	0.0320	-0.0214	0.3366	-0.6200	0.7663
ULS	24 (13.56)	0.4790	0.5443	0.3282	-0.3884	1.0057
PPP	12 (6.78)	0.1787	0.1680	0.2878	-0.3039	0.7206
Misericordia	40 (22.60)	-0.7446	-0.6310	0.6966	-2.2428	0.4629
Medical teaching						
Teaching	24 (13.56)	-0.1844	-0.2116	0.2010	-0.5040	0.3151
Non-Teaching	153 (86.44)	-0.0516	0.1237	0.6370	-2.2428	1.0057
Dimension						
Beds<=200	60 (33.90)	-0.4380	-0.2738	0.7562	-2.2428	0.8672
200<Beds<=400	60 (33.90)	0.2707	0.2680	0.3781	-0.5636	1.0057
400<Beds<=600	27 (15.25)	0.1301	0.0787	0.3080	-0.5098	0.7388
600<Beds<=800	14 (7.91)	-0.1748	-0.1575	0.2605	-0.6067	0.3432
Beds>800	16 (9.04)	-0.2093	-0.2454	0.2320	-0.6200	0.3151
Location						
North	75 (42.37)	-0.2537	-0.0968	0.7580	-2.2428	1.0057
Center	39 (22.03)	0.0139	0.0852	0.4292	-1.0483	0.7388
Lisbon and Tagus Valley	48 (27.12)	0.0289	0.0932	0.3473	-0.6303	0.7206
Alentejo	12 (6.78)	0.3916	0.5381	0.3830	-0.3884	0.8672
Algarve	3 (1.69)	0.0257	0.1814	0.3911	-0.4192	0.3151
TOTAL	177 (100)	-0.0696	0.0161	0.5981	-2.2428	1.0057

higher indexes β^{index} provide poorer access to surgery (higher waiting times).

To make the model as flexible as possible and account for possible nonlinearities we treated all variables as categorical, that is, we included a dummy variable for each variable's category. Since some of the variables are of high dimension (have a large number of categories), we opted to employ a high-dimensional fixed effect algorithm to overcome the computational restraints, as proposed by Guimarães and Portugal (2010).

Table 3.2 reports descriptive statistics for the waiting time index across several dimension of hospital-specific characteristics.[4]

The statistics show that hospitals from ULSs have, on average, longer waiting times in contrast to Misericordia's hospitals that present the shortest waiting times. The index also suggests that medical teaching hospitals have shorter waiting times than non-teaching hospitals. Surprisingly, intermediate-sized hospitals (between 200 and

[4]Table A3.1 in the Appendix shows the list of hospitals included in this study.

600 beds) seem to have the longer waiting times when compared to either smaller or larger hospitals.

In terms of regional disparities, we find that the North region has, on average, hospitals with much shorter waiting times, while, on the other hand, Alentejo has the longest waiting times. However, it is important to note that the concentration of Misericordia's hospitals is higher in the North, and that hospitals in Alentejo are mostly ULSs.

3.3.3 Spatial econometric approach

After estimating the hospitals' waiting time index, we move to the second step of the econometric approach, where we employ spatial panel models to test for spatial interactions among hospitals. Given that the hospital index is allowed to change over time we employ a panel data approach. This also has the advantage of permitting the use of a larger number of observations.

The general spatial model is given by (Belotti et al., 2017; Elhorst, 2014):

$$\boldsymbol{Y}_t = \rho \boldsymbol{W}\boldsymbol{Y}_t + \alpha \boldsymbol{\imath}_N + \boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}_t\boldsymbol{\theta} + \boldsymbol{\mu} + \boldsymbol{u}_t \tag{3.6}$$

$$\boldsymbol{u}_t = \lambda \boldsymbol{W}\boldsymbol{u}_t + \boldsymbol{\varepsilon}_t \tag{3.7}$$

where the vector $\boldsymbol{Y}_t$ corresponds to the hospital's waiting time index by year, obtained from eq. 3.5. $\boldsymbol{W}$ is a matrix of spatial weights and thus $\boldsymbol{W}\boldsymbol{Y}_t$ shows the endogenous spatial interaction effects. The matrix $\boldsymbol{W}\boldsymbol{X}_t$ represents the exogenous spatial interaction effects while $\boldsymbol{W}\boldsymbol{u}_t$ stands for the spatial interaction effects among the disturbance term.[5] ρ is the spatial autoregressive coefficient, λ the spatial autocorrelation coefficient, $\boldsymbol{\theta}$ and $\boldsymbol{\beta}$ are parameters to be estimated, and α is the constant term parameter. $\boldsymbol{\mu} = (\mu_1, \ldots, \mu_N)^T$ corresponds to spatial (hospital) specific effects. Finally, $\boldsymbol{\varepsilon}_t$ is a perturbation term that follows the standard assumptions.

In line with the literature (as explained in Section 2), we estimate hospital reaction

[5]For ease of exposition we assume that the spatial matrix is the same for every term and for every time period but that assumption could be relaxed.

functions, in which spatial interactions among dependent variables are assumed. Thus, we restrict our interest to two types of spatial econometric models: the spatial lag model (SAR) where $\rho \neq 0$; $\boldsymbol{\theta} = \mathbf{0}$ and $\lambda = 0$; and the spatial Durbin model (SDM) where $\rho \neq 0$; $\boldsymbol{\theta} \neq \mathbf{0}$ and $\lambda = 0$.

Both specifications are shown below, respectively (Belotti et al., 2017; Elhorst, 2014):

$$\boldsymbol{Y}_t = \rho \boldsymbol{W} \boldsymbol{Y}_t + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\epsilon}_t \tag{3.8}$$

$$\boldsymbol{Y}_t = \rho \boldsymbol{W} \boldsymbol{Y}_t + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{X}_t \boldsymbol{\theta} + \boldsymbol{\mu} + \boldsymbol{\epsilon}_t \tag{3.9}$$

Clearly, the SAR model is a particular case of the SDM. Estimation of a fixed or random effects model depends on the assumptions regarding $\boldsymbol{\mu}$. In the fixed effects model, the $\boldsymbol{\mu}$ have no specific parametric form and can be possibly correlated with other explanatory variables. Thus, they can be estimated by adding a dummy variable for each hospital. Since some of our explanatory variables are time-invariant or have a very small amount of variation over time, the coefficient associated with those variables could not be estimated with a fixed effects specification. Hence, we opted to estimate only the random effects version of the spatial panel models. Here, the spatial effects are assumed to be random variables (independently and identically distributed), with $\boldsymbol{\mu} \sim N\left(0, \sigma_{\mu}^2\right)$ (Elhorst, 2014).

Our estimation strategy is the following. We start with a simple random effects specification (benchmarking) that excludes spatial interactions. If the random effects are justified then we add interactions only for the dependent variable and thus estimate a SAR model with random effects. This means that if $\rho = 0$ there is no evidence of spatial interactions in the dependent variables and the simple random effects model is preferable. Finally, we estimate the more general SDM model that assumes endogenous and exogenous spatial effects. If the spatial exogenous effects are significant then we should consider the SDM model; otherwise, the SAR model is considered to be the most suitable. If $\rho = 0$ and $\boldsymbol{\theta} = 0$ we should estimate the simple random effects model. Both spatial panel models are estimated using quasi-maximum likelihood methods as explained in (Belotti et al., 2017).

For the spatial panel models we can analyse either direct or indirect effects (also known as spillover effects) (Elhorst, 2014). In the SAR model (eq. 3.8), the direct effect measures the impact, for instance, of an independent variable of hospital A on the explained variable of the same hospital. The spillover effect occurs among the dependent variables, that is, how waiting times of hospital A interacts with waiting time of hospital B.

In the SDM model (eq. 3.9), the direct effect is identical to that of the SAR model. However, there are two indirect effects to be assessed. One of them corresponds to the indirect impact of the SAR model; the other indirect effect is the impact of an independent variable from hospital A on hospital B waiting times.

The ρ is the spatial lag parameter and is interpreted as the slope of the reaction function. If $\rho > 0$ waiting times are complementary, if $\rho < 0$ they are assumed to be substitutes and if $\rho = 0$ it is assumed that they are independent (Gravelle et al., 2014).

The econometric analysis was implemented with Stata 14. We used the user written "spatwmat" command (Pisati, 2001) to compute the spatial weight matrix and the user-written "xsmle" command to estimate the spatial-panel models (Belotti et al., 2017).

The spatial weights matrix

W corresponds to the spatial weight matrix. We opted to construct a weight matrix based on the inverse of time distance between the hospitals. Using Google maps we collected time distances for every pair of hospitals. However, we only considered relevant distances that were below the threshold of 90 minutes[6]. Thus, the generic element W_{ij} of the matrix linking hospital i and j is given by:

$$W_{ij} = \begin{cases} 0 \text{ if } i = j \\ \frac{1}{d_{ij}} \text{ if } d_{ij} \leq 90\text{min and } i \neq j \\ 0 \text{ if } d_{ij} > 90\text{min and } i \neq j \end{cases} \tag{3.10}$$

Hospitals that are within 90 minutes distance of each other have a lower weight the

[6]We chose an area of competition up to 90 minutes, according to the studies of ERS (2014) and ERS (2012b).

greater the distance between them. Hospitals that are outside of the 90 minute range are assumed to exert no influence on each others outcomes and consequently we set the corresponding weight to 0. It is also noteworthy that the spatial matrix must be normalised so that the sum of the row is equal to one.

To ensure consistent results, we also used the inverse distance squared spatial weights matrix to penalize longer distances. We conclude that there are no significant differences to report between the use of the two matrices.

Explanatory variables

We add variables that aim to capture the effect of the hospital type of ownership/ management and the hospital service organisation model, as explained in section 3.2. Since the organisational models (i.e., CHs, ULSs, IPOs, "hospital units") are part of the public sector management, we reduce the type of ownership/management and the hospital organisation into one group, as shown in Table 3.3.

We add the number of beds as a proxy for hospital inputs employed in surgery[7]. Because there was a lack of data on this variable for Misericordia's hospitals, we construct intervals for the number of beds and include those hospitals in the range below 200 beds.

The number of specialities per hospital is also included based on the microdata provided by ACSS. Since the number of specialities is strongly correlated with the hospital dimension (number of beds), i.e. larger hospitals offer a higher number of specialities, we opted to include only the specialities into the models.

We add the hospitals' collaboration with universities in medical teaching as its relevance is recognised in creating new knowledge and improving the healthcare provided to patients (Ayanian and Weissman, 2002). In this category we include the following hospitals: CH Algarve, CH Cova da Beira, CH Lisboa Central, CH Lisboa Norte, CH Porto, CH São João, CH Coimbra and H Braga.

The descriptive statistics for the spatial models are in Table 3.3.

[7]The information was obtained in http://benchmarking.acss.min-saude.pt/MH_CapacidadeUtilizadaDashboard.

Table 3.3: Summary statistics for spatial econometric models

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent variable					
Waiting time índex	177	-0.0696	0.5981	-2.2428	1.0057
Independent variables					
Organisational structure					
IPO (0/1)	177	0.0508	0.2203	0	1
Hospital (0/1)	177	0.1638	0.3712	0	1
CH (0/1)	177	0.3559	0.4802	0	1
ULS (0/1)	177	0.1356	0.3433	0	1
PPP (0/1)	177	0.0678	0.2521	0	1
Misericordia (0/1)	177	0.2260	0.4194	0	1
Medical teaching					
Teaching (0/1)	177	0.1356	0.3433	0	1
Non-Teacning (0/1)	177	0.8644	0.3433	0	1
Dimension					
Beds<=200 (0/1)	177	0.3390	0.4747	0	1
200<Beds<=400 (0/1)	177	0.3390	0.4747	0	1
400<Beds<=600 (0/1)	177	0.1525	0.3606	0	1
600<Beds<=800 (0/1)	177	0.0791	0.2707	0	1
Beds>800 (0/1)	177	0.0904	0.2876	0	1
Specialities	177	9.3672	4.1211	2	25

3.4 Results

Table 3.4, Table 3.5 and Table 3.6 show the estimates of the three random effects models, namely, the linear regression, the spatial lag and the spatial Durbin model. We consider three different specifications. In the first column, Column A, we control for the hospitals' organisational structure only. In column B we add the variable medical teaching. Finally, in column C we include the number of specialities as a proxy for the hospital dimension.

The simple random effects model[8](Table 3.4) is consistent in indicating that Misericordia's hospitals have lower waiting times and that the ULSs (reference category) have the longest waiting times. The results also show that hospitals with medical teaching have shorter waiting times, although in specification C, when we control for the number of specialities, the variable is only significant at the 10% level. Hospital dimension is not statistically significant to explain the waiting time index.

[8]It should be noted that in the absence of spillover effects in the simple random effects model, the coefficients presented in Table 3.4 should be compared with the direct effects of the spatial models.

Table 3.4: Estimation of OLS model for waiting time index

Variables	A	B	C
Organisational structure			
IPO	-0.3251	-0.3251	-0.3037
Hospital	-0.6685***	-0.6620***	-0.6676***
CH	-0.4470***	-0.3314**	-0.3154***
Misericordia	-1.0755***	-1.0802***	-1.0914***
PPP	-0.3003*	-0.2136	-0.2096
Medical teaching			
Yes		-0.3466***	-0.2941*
Hospital dimension			
Number of specialities			-0.0089
cons	0.4790***	0.4790***	0.5520***
Obs	177	177	177
Hospitals	59	59	59
T	3	3	3
R2	0.4080	0.4406	0.4428
Wald	36.66***	52.75***	52.25***
Test for random effects	110.51***	107.12***	105.81***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table 3.5: Estimation of the spatial lag model for waiting time index

	A	B	C
ρ	0.4324***	0.4600***	0.4590***
Control Variables			
Organisational structure	X	X	X
Medical teaching		X	X
Hospital Dimension (with number of specialities)			X
Obs	177	177	177
Hospitals	59	59	59
T	3	3	3
R2	0.3840	0.4393	0.4413
Log PseudoL	-37.2877	-34.6251	-34.4739

$^{***}p < 0.01$

Table 3.6: Estimation of the spatial Durbin model for waiting time index

	A	B	C
ρ	0.4792***	0.4746***	0.4780***
Test of $\boldsymbol{WX}$	14.95**	7.36	8.70
Control Variables			
Organisational structure	X	X	X
Medical teaching		X	X
Hospital Dimension (with number of specialities)			X
Obs	177	177	177
Hospitals	59	59	59
T	3	3	3
R2	0.3781	0.4137	0.4193
Log PseudoL	-33.7334	-31.9818	-31.5910

$^{***}p < 0.01$, $^{**}p < 0.05$

The Breusch and Pagan Lagrangian multiplier test for random effects indicates that random effects are significant at the 1% level (in the three specifications) and that a simple OLS specification should be rejected.

We next move to the SAR model with random effects (Table 3.5) to infer whether the pattern of endogenous spatial dependence is significant. The results indicate that, in the three specifications, there is a positive and significant estimate for the spatial lag parameter indicating complementarity between waiting times of neighbouring hospitals. In other words, when waiting times change in a given hospital, waiting times follow the same pattern in neighbouring hospitals (and vice versa). It is also noteworthy that the statistical significance of the spatial coefficient reveals that we should favour this specification against the simpler random effects model.

We also considered the spatial Durbin model with random effects (Table 3.6) that includes both endogenous and exogenous spatial interaction effects. The results are in line with those of the SAR model, showing a positive and significant sign for the spatial lag coefficient across all specifications. However, with the exception of the simpler specification in column A, we did not find statistical evidence favouring the presence of exogenous spatial interaction effects. Given these results our preference goes for the analysis of the SAR model in Table 3.5.

Hence, we next decompose the estimates of the spatial lag model (specification C) into direct and indirect effects. Recall, that the direct effect corresponds to the impact

Table 3.7: Direct, indirect, and total effects based on the spatial lag model for waiting time index

	Coefficient	Robust Std. Error
Direct Effects		
IPO	-0.2597	0.2698
Hospital	-0.6607***	0.2371
CH	-0.2887**	0.1407
Misericordia	-1.0746***	0.2114
PPP	-0.1731	0.1745
Teaching	-0.3897**	0.1525
Hospital Dimension (with number of specialities)	-0.0090	0.0189
Indirect Effects		
IPO	-0.2265	0.2717
Hospital	-0.5868 *	0.3477
CH	-0.2523	0.1667
Misericordia	-0.9213**	0.3689
PPP	-0.1554	0.1769
Teaching	-0.3383*	0.1844
Hospital Dimension (with number of specialities)	-0.0074	0.0163
Total effects		
IPO	-0.4861	0.5281
Hospital	-1.2475**	0.5565
CH	-0.5410*	0.2933
Misericordia	-1.9959***	0.5197
PPP	-0.3285	0.3437
Teaching	-0.7280**	0.3180
Hospital Dimension (with number of specialities)	-0.0164	0.0348

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

of hospital-specific variables on their waiting times. On the other hand, indirect effect measures spillovers effects – they analyse how hospitals' waiting times influence the waiting times of neighbouring hospitals. The estimates are shown in Table 3.7.

Table 3.7 shows that the estimates of direct effects are in line with the coefficients presented in Table 3.4. Thus, it is shown that the Misericordia's hospitals have the lowest waiting times indexes, followed by the "hospital units" and the CHs. It should also be noted that the difference between Misericordia's hospitals and "hospital units" is statistically significant, as well as the difference between "hospital units" and CHs. The estimates also show that medical teaching hospitals have lower waiting time index (at the 1 % level) compared with non-medical teaching hospitals.

Regarding the spillover effects, we find a significant impact of Misericordia's hospitals, meaning that the waiting times of Misericordia's hospitals also contribute to reducing the waiting times of neighbourhoods. "Hospital units" and medical teaching hospitals also present a significant spillover effect although at a significance level of only 10%.

Finally, the hospital dimension is not significant in either direct and indirect effects[9].

3.5 Spatial dependence with cancellations

In this section, we explore another dimension for the existence of spatial competition. Since we have information on cancellations along with the surgery episodes we can verify whether higher rates of cancellation in a given hospital impact on neighbouring ones.

It should be noted that hospitals may have shorter waiting times because they have higher cancellation rates on events with longer waiting times. Thus, the main question in this section is to understand whether there are also interactions in terms of cancellations.

We use the same patient-level data as in section 3, to which we added information on cancellations. Appendix - Table A3.2 shows the cancellation rate for the most relevant patients' characteristics.

To construct a hospital-specific cancellation index, we follow a similar approach as we did for constructing the waiting time index. In the first step, we estimate a Linear Probability Model (LPM) [10] based on patient-level data. The model specification is defined as follows:

[9] We have estimated the direct and indirect effects without the variable hospital dimension, and we find the same conclusions.

[10] We have estimated a LPM because it gives us greater flexibility and because our main interest lies in the coefficients estimation of hospital and year interaction. We also estimate a logit model, however, for computational reasons and to avoid the incidental parameter bias we could not use a highly flexible parametric functional form with a dummy variable added for each single category of every variable as we did when computing the hospital waiting time index and the LPM. Some restrictions had to be imposed on the variables in order to estimate a logit model. For the variable age, we created six age groups: below 15 years old; from 15 to 29; from 30 to 44; from 45 to 59; from 60 to 74; above 75 years. Likewise, since there are thousands of categories on surgical procedures, we used dummy variables for the 300 most common surgical procedures, and we coded the remaining as "others".

$$\textbf{Cancellation} = \boldsymbol{\beta}^{\text{index canc}}\, \textbf{Hospital} * \textbf{Year} + \mathbf{X}\boldsymbol{\beta}^{\text{COV}} + \boldsymbol{\varepsilon} \tag{3.11}$$

where Cancellation is a binary variable, that takes 1 for patient cancellation, and 0 otherwise. $\boldsymbol{\beta}^{\text{index canc}}$ measures the risk of hospital cancellation by year. Hospitals with higher $\boldsymbol{\beta}^{\text{index canc}}$ are expected to provide their patients worse health care in a specific year. $\mathbf{X}$ is a vector of covariates to control for several sources of patient level heterogeneity.

In line with Section 3, we employ the high-dimensional fixed effect algorithm and we include variables that may be relevant to explain the probability of cancellation. Those variables are such as the speciality, surgical procedure, patient's priority, or cancer indicator. We also add the patient's age, gender and municipality because they may be associated with patients specific factors that make them more exposed to cancellation (e.g., number of comorbidities associated with aging; distance to hospital).

Table 3.8 reports the descriptive statistics for cancellation probability index (obtained in eq. 3.11) by hospital-specific variables. The statistics that stand out are the reduced cancellation index presented by Misericordia's hospitals and PPP's hospitals. Thus, the results show that the Misericordia's hospitals in addition to having a lower waiting time index, they also present a good performance in the surgery rate.

The statistics also show that North has lower rates of surgeries' cancellation. On the other side, Alentejo and Algarve have hospitals with the highest cancellation rates. Smaller hospitals have lower cancellation rates than other sized hospitals, and hospitals with medical teaching have higher cancellation rates.

Next, we estimate the same models at the level of the hospitals as we did before,but now the cancellation index is the dependent variable (recall that in section 3, we have the waiting time index as the dependent variable).

Table 3.9 shows the results of the SAR model (the estimations for OLS can be found in Appendix - Table A3.3). As in the previous section, the results show a positive endogenous spatial dependence, although without statistical significance.

The coefficient sign of the endogenous spatial dependence changes in the estimation of the spatial Durbin model, although this is not statistically significant (see Table 3.10).

Table 3.8: Summary statistics for cancellation probability index by hospital-specific variables

Variables	Mean	Median	Std. Dev.	Min.	Max.
Organisational structure					
IPO	0.0078	0.0037	0.0276	-0.0264	0.0468
Hospital	0.0074	0.0125	0.0355	-0.0754	0.0770
CH	0.0029	-0.0012	0.0305	-0.0465	0.1038
ULS	0.0016	-0.0017	0.0407	-0.0550	0.1248
PPP	-0.0376	-0.0313	0.0223	-0.0833	-0.0089
Misericordia	-0.0957	-0.1098	0.0490	-0.1679	0.0373
Medical teaching					
Teaching	0.0084	0.0031	0.0337	-0.0421	0.0672
Non-Teaching	-0.0260	-0.0161	0.0568	-0.1679	0.1248
Dimension					
Beds<=200	-0.0670	-0.0770	0.0603	-0.1679	0.0770
200<Beds<=400	0.0005	0.0015	0.0342	-0.0597	0.1248
400<Beds<=600	-0.0038	-0.0012	0.0326	-0.0833	0.0503
600<Beds<=800	-0.0024	-0.0088	0.0366	-0.0421	0.1038
Beds>800	0.0219	0.0156	0.0321	-0.0281	0.0672
Location					
North	-0.0444	-0.0267	0.0563	-0.1470	0.0368
Center	-0.0082	-0.0100	0.0463	-0.1079	0.1038
Lisbon and Tagus Valley	-0.0088	0.0031	0.0479	-0.1679	0.0580
Alentejo	0.0090	-0.0021	0.0530	-0.0550	0.1248
Algarve	0.0638	0.0642	0.0036	0.0600	0.0672

Table 3.9: Estimation of the spatial lag model for cancellation index

	A	B	C
ρ	0.0383	0.0353	0.0342
Control Variables			
Organization structure	X	X	X
Medical teaching		X	X
Hospital Dimension (with number of specialities)			X
Obs	177	177	177
Hospitals	59	59	59
T	3	3	3
R2	0.5625	0.5693	0.5681
Log PseudoL	360.3595	361.0614	361.2313

Table 3.10: Estimation of the spatial Durbin model for cancellation index

	A	B	C
ρ	-0.0650	-0.0441	-0.0281
Test of $\boldsymbol{WX}$	7.97	13.81**	17.80**
Control Variables			
Organisational structure	X	X	X
Medical teaching		X	X
Hospital Dimension (with number of specialities)			X
Obs	177	177	177
Hospitals	59	59	59
T	3	3	3
R2	0.5890	0.6083	0.6157
Log PseudoL	363.2290	365.2649	365.9203

$^{**}p < 0.05$

Table 3.10 also shows that exogenous spatial dependence is statistically significant, so we use Durbin's model (specification C) for the analysis of direct and indirect effects. The estimations are shown in Table 3.11.

Recall that the interpretation of the direct effect is similar to the SAR model, but the indirect effects comprise the endogenous and exogenous spatial effects. Since the spatial endogenous interaction is not significant, the spillover effects are mostly driven by exogenous spatial interactions. Thus, for simplification, the indirect effect corresponds to the impact of an independent variable of hospital A in the hospital B's output.

Table 3.11 shows that Misericordia's hospitals have, on average, lower cancellation indexes, followed by PPPs hospitals (see the direct effect). It is also noteworthy that the difference between Misericordia's hospitals and PPP's hospitals is statistically significant. However, neither has statistical significance in the indirect effects.

On the other hand, the estimates show that IPOs are less likely to have surgery (direct effect), but have no spillover effects on neighbouring hospitals.

Although medical teaching hospitals have no significant direct effects, they are the only ones that have a significant spillover effect in the cancellation index, contributing to a reduction in the cancellation rate of neighbouring hospitals.

As in the estimation of spatial models with waiting time indexes, the hospital dimension is once again not statistically significant in either direct or indirect effects[11].

To check the results robustness, Appendix - Table A3.4 shows the direct/indirect effects if we had used the logit model to obtain the cancellation index. The main difference to be reported is that Misericordia's hospitals have no longer an insignificant indirect effect. The size of the hospital also becomes relevant to explain spillover effects and total effects as well. However, as mentioned before, the logit model would imply a set of constraints, so we opted for the LPM for providing higher flexibility.

3.6 Discussion

Our study analyses the strategical interactions between hospitals regarding the access to scheduled NHS surgeries. We estimated two hospital indexes for the waiting times and cancellations, derived from patient-data. All the results show the existence of spillover effects for both indexes.

We find a consistent and positive endogenous spatial dependence for waiting times. It means that, when a given hospital's waiting times change, the neighbouring hospital's index moves in the same direction (and vice versa).

Thus, the waiting times to scheduled surgery are shown to be strategic complements. These findings point out that there are hospital spillovers that should be used to improve access to scheduled surgery, which is in line with the Gravelle et al. (2014)'s paper that finds the quality improvement in a hospital has, for some quality measures, positive

[11] We have estimated the direct and indirect effects for the cancellation index without the variable hospital dimension, and we find the same conclusions.

Table 3.11: Direct, indirect and total effects based on the spatial Durbin model for cancellation index

	Coefficient	Robust Std. Error
Direct Effects		
IPO	0.0362**	0.0160
Hospital	-0.0139	0.0165
CH	-0.0200	0.0165
Misericordia	-0.1018***	0.0186
PPP	-0.0515***	0.0191
Teaching	-0.0132	0.0147
Hospital Dimension (with number of specialities)	0.0012	0.0014
Indirect Effects		
IPO	0.0339	0.0343
Hospital	-0.0288	0.0635
CH	-0.0353	0.0386
Misericordia	-0.0455	0.0301
PPP	0.0496	0.0845
Teaching	-0.0984**	0.0496
Hospital Dimension (with number of specialities)	-0.0022	0.0038
Total effects		
IPO	0.0701*	0.0367
Hospital	-0.0426	0.0641
CH	-0.0553	0.0497
Misericordia	-0.1473***	0.0320
PPP	-0.0019	0.0881
Teaching	-0.1117*	0.0562
Hospital Dimension (with number of specialities)	-0.0011	0.0042

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

spillover effects in neighbouring hospitals.

Regarding the cancellation index, we are able to find an exogenous spatial dependence although only medical teaching hospitals have a statistically significant spillover effect.

We also found that Misericordia's hospitals have the shortest waiting time index and the highest impact on neighbouring hospital's waiting times. Although they have no spillover effects regarding the cancellation index, Misericordia's hospitals also show the lowest cancellation index.

These gains achieved by Misericordia's hospitals are not surprising since the co-operation with Misericordia's hospitals is intended to improve access and efficiency (Almeida, 2017). Thus, the results point towards the need to develop a strengthening cooperation between NHS and Misericordia's hospitals in order to improve access to surgery for more patients.

The estimations also indicate that PPPs are not statistically relevant in explaining the waiting time index (both direct and indirect effects). On the other hand, it is shown that they have lower cancellation indexes (direct effect), although the total effect is not statistically significant. The results are not clear about the advantages in scheduled surgery brought by PPP's hospitals. Thus, this result is in line with the main findings of a study performed by ERS (2016) that evaluates the PPP's performance and it takes into account four measures - relative efficiency, efectiveness, quality and regulation costs, but it achieves no overall conclusions regarding the advantages or disadvantages of PPP management.

Medical teaching hospitals are relevant in terms of spillover effects for both waiting times and cancellations indexes. This result corroborates the relevance of teaching hospitals in improving the surgical performance of neighbouring hospitals, due to knowledge dissemination effects.

As nowadays it is observed that demand for health and surgery has increased not only in Portugal but in several OECD countries, policymakers should consider increasing its supply so that patients' health is not adversely affected (Siciliani et al., 2013). It is also recognised that such supply increases may not include new public hospital's building due to budget constraints. Instead, extra funding for surgery activity within the NHS may be considered for cases where hospitals are operating way below full capacity (e.g. additional health staff, extending working hours). Moreover, in our view, the agreements with the social sector (for minor surgeries) should be promoted, given the good performance that Misericordia's hospitals display.

We should mention again that, for the period in question, there was no free patient's choice. Therefore, it is suggested that this analysis may be extended in future research to more recent periods to verify the spatial pattern's consistency.

One can state free choice increases hospital competition and reduces waiting times. However, Brekke et al. (2008)'s study shows hospital's competition (caused by patient choice) increased waiting times because hospitals competed to treat high-benefit patients rather than unprofitable patients.

For example, Simões et al. (2017)'s research analyses the implications of the 2016 reform that introduced free patient choice in the Portuguese NHS. The authors draw identical conclusions, i.e., hospitals that received most referrals out of their area have longer waiting times than before for the first consultation.

In our opinion, this topic deserves further analysis. First, to observe whether there was a significant increase in free patient's choice since 2016 in the Portuguese NHS, that is, to see how many patients had surgery outside their area of residence, controlling for a set of hospital's and patient's characteristics. Second, to infer whether free patient's choice contributed to increasing strategic interactions among hospitals and how it impacted surgeries' waiting times and cancellations as well.

3.7 Conclusion

This research analyses Portuguese NHS hospitals between 2013 and 2015, and it measures the spatial dependence among hospitals in the waiting times for surgery and the probability of cancellation as well.

We have constructed two hospital indexes (as a proxy for hospital quality) derived from patient-data, and our results are consistent in showing spillover effects for both indexes. Furthermore, our study identifies the hospitals' features that seems to be crucial in explaining spillovers.

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Appendix

Table A3.1: Hospitals in the sample

Hospital entity	Region
CH Algarve	Algarve
CH Baixo Vouga	Center
CH Barreiro Montijo	Lisbon and Tagus Valley
CH Cova da Beira - Covilhã	Center
CH Entre o Douro e Vouga	North
CH Leiria	Center
CH Lisboa Central	Lisbon and Tagus Valley
CH Lisboa Norte	Lisbon and Tagus Valley
CH Lisboa Ocidental	Lisbon and Tagus Valley
CH Médio Ave - Famalicão	North
CH Médio Tejo -T. Novas	Lisbon and Tagus Valley
CH Oeste	Lisbon and Tagus Valley
CH Porto	North
CH Póvoa do Varzim/VC	North
CH Setúbal	Lisbon and Tagus Valley
CH São João	North
CH Tondela - Viseu	Center
CH Trás-os-Montes e Alt. Douro	North
CH Tâmega e Sousa	North
CH Univer. de Coimbra	Center
CH V. Nova de Gaia/Espinho	North
H Arc. J. Crisóst. - Cantanhede	Center
H Beatriz Ângelo - Loures, PPP	Lisbon and Tagus Valley
H Braga, PPP	North
H D. Figueira da Foz	Center
H D. Santarém	Lisbon and Tagus Valley
H Dr. Franc. Zagalo - Ovar	Center
H Espírito Santo - Évora	Alentejo
H Fern. da Fonseca - Lx	Lisbon and Tagus Valley
H Garcia de Orta - Almada	Lisbon and Tagus Valley
H José Luc. de Castro - Anadia	Center
H Miser. de Fão	North
H Miser. de Lousada	North
H Miser. de Mealhada	Center
H Miser. de Vila Verde	North
H Miser. de Vila do Conde	North
H Prelada	North
H Sra da Oliveira - Guimarães	North
H Sta Maria Maior - Barcelos	North
H V. F. Xira, PPP	Lisbon and Tagus Valley
HPP - H Cascais, PPP	Lisbon and Tagus Valley
IPO Coimbra	Center
IPO Lisboa	Lisbon and Tagus Valley
IPO Porto	North
Sta Casa M. Entronc. - H. S. J. Baptista	Lisbon and Tagus Valley
Sta Casa M. Esposende - Valentim Ribeiro	North
Sta Casa M. Felgueiras - H. Agost. Ribeiro	North
Sta Casa M. M. de Canaveses	North
Sta Casa M. P. de Lanhoso - H. Ant. Lopes	North
Sta Casa M. R. d'Ave - H. Narciso Ferreira	North
Sta Casa M. de Benavente	Lisbon and Tagus Valley
ULS Alto Minho - V. Castelo	North
ULS Baixo Alentejo - Beja	Alentejo
ULS Castelo Branco	Center
ULS Guarda	Center
ULS Litoral Alent. - Sant. Cacém	Alentejo
ULS Matosinhos	North
ULS Nordeste - Bragança	North
ULS Norte Alentejano - Portalegre	Alentejo

Table A3.2: Cancellation rate by patient characteristics

Variable	Surgery	Cancellation	Cancellation rate (%)
Gender			
Female	936,521	151,043	13.89
Male	701,843	115,069	14.09
Cancer			
Yes	135,161	13,094	8.83
No	1,503,202	253,018	14.41
Priority			
1	1,249,863	226,455	15.34
2	268,818	28,532	9.60
3	70,581	6,440	8.36
4	49,102	4,685	8.71
Age groups			
<15 years	95,801	12,936	11.90
[15,30[	107,743	20,435	15.94
[30,45[	236,659	41,290	14.86
[45,60[	373,547	59,711	13.78
[60,75[	473,225	71,823	13.18
>=75 years	351,389	59,917	14.57

Table A3.3: Estimation of OLS model for cancellation index

Variables	A	B	C
Organisational structure			
IPO	0.0062	0.0062	0.0038
Hospital	-0.0029	-0.0029	-0.0030
CH	0.0013	-0.0040	-0.0058
Misericordia	-0.0910***	-0.0910***	-0.0892***
PPP	-0.0392**	-0.0431***	-0.0435***
cons	0.0016	0.0157	0.0010
Medical teaching			
Yes		0.0157	0.0098
Hospital dimension			
Number of specialities			0.0010
Obs	177	177	177
Hospitals	59	59	59
T	3	3	3
R2	0.5605	0.5679	0.5664
Wald	61.17***	62.40***	61.97***
Test for random effects	53.21***	51.71***	51.89***

$^{***}p < 0.01$, $^{**}p < 0.05$

Table A3.4: Direct, indirect and total effects based on the spatial Durbin model for cancellation index obtained from the logit model

	Coefficient	Robust Std. Error
Direct Effects		
IPO	0.2429***	0.0872
Hospital	-0.0591	0.0856
CH	-0.0950	0.0897
Misericordia	-0.4224***	0.0945
PPP	-0.2638***	0.1019
Teaching	-0.0076	0.0686
Hospital Dimension (with number of specialities)	-0.0023	0.0069
Indirect Effects		
IPO	0.1929	0.1475
Hospital	-0.0647	0.3788
CH	-0.0313	0.2235
Misericordia	-0.3959***	0.1499
PPP	0.3804	0.4052
Teaching	-0.5150**	0.2533
Hospital Dimension (with number of specialities)	-0.0372*	0.0197
Total effects		
IPO	0.4358**	0.1715
Hospital	-0.1239	0.3741
CH	-0.1263	0.2686
Misericordia	-0.8183***	0.1441
PPP	0.1165	0.4379
Teaching	-0.5226*	0.2786
Hospital Dimension (with number of specialities)	-0.0395*	0.0227

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Conclusion

In the previous chapters, we discussed different topics related to the waiting times for scheduled surgery in the Portuguese NHS, that has allowed us to elicit some conclusions regarding the functioning of the Portuguese health system. Thus, we believe that there are some recommendations that, if implemented, could help ensure better equity in terms of access to health care. Below, we elaborate on those.

Regarding waiting times for surgery by gender, we found an unexplained difference in waiting times between men and women of 3%. Although the estimate for gender gap is much smaller further investigation should be carried to understand what is at the source of the difference between genders.

On the other side, our methodology helped us to understand that clinical priority is the main reason why men have shorter waiting times for surgery. This result could be explained by the fact that when men are evaluated they display worse clinical conditions and as such, have higher clinical prioritisation compared with women. In this way, we can suggest that there should be higher monitoring of men's health, particularly primary health care and occupational medicine, to reduce risky behaviours or so that their pathology could be identified at an earlier stage.

When we study access to surgery by analysing surgical episodes along with cancellation episodes, the hypothesis that men present a worse clinical conditional seems to be corroborated. That is, in addition to finding out that men display a higher hazard rate for time to surgery, they are also shown to have a higher probability that the cancellation is due to patient's death.

The results also allowed us to conclude that patient's prioritisation holds for the Portuguese NHS, since patients with higher priority have shorter waiting times. However, we found that patients with most severe priorities have a higher risk of cancelling because they had surgery before, which suggests that their condition was so severe that it was not possible to meet it in a timely manner. Also, we found that the priority noncompliance percentage is higher for cancellations rather than for surgery episodes, and that priority noncompliance is relevant to explain the type of cancellation. Thus, this result reinforces the need to meet each priority waiting times, since priority noncompliance is a barrier in access to surgery.

Moreover, the research on spatial analysis allowed us to conclude that Misericórdia's hospitals are those with the best performance levels, also showing beneficial spillover effects. Agreements with Misericórdia's hospitals should be strengthened for lower priority surgeries so that scheduled surgery access and patient's prioritisation compliance are improved, since building new hospitals to increase surgery supply may not be financially feasible. In addition, these agreements could help public hospitals to improve patients' priorities management.