

**ESSAYS ON HEALTH ECONOMICS:
EQUITY AND ACCESS TO HEALTH CARE AND PUBLIC
HOSPITAL PERFORMANCE UNDER CORPORATIZED
MANAGEMENT**

by

César Alberto dos Santos Carneiro

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Thesis Adviser: Professor Doutor Nuno Sousa Pereira

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À minha mulher Helena e ao meu filho Gabriel

Ao meu pai, à minha mãe e ao meu irmão

BIOGRAPHICAL NOTE

I was born in March 1981, in Porto, Portugal, a city that has been the focal point of all my academic, professional and personal life. I'm married since 2009 and just about to have my first child.

In my first years of education I was taught at 'Externato de Camões', a private school with a rigorous and demanding education style that I now acknowledge as having been determinant for all my academic course. My high school years were spent in public school, in the pre-specialized field of economics and social sciences, having completed this block of years with a classification of 18 in a scale up to 20.

In 1999 I was admitted in the undergraduate course in Economics at the Faculty of Economics of the University of Porto (FEP). I finished this 5-year course in 2004 with the final classification of 14. The excellent professors I encountered in the faculty and the vast curricula of this course impelled me to proceed to graduate studies in this field. Thus, in September 2004 I was admitted to the 'Master's in Economics' postgraduate course at FEP. In that same year I simultaneously began to work at the marketing department of one of the most important telecommunications companies in Portugal, Optimus SA. I worked there for one year, a period during which I completed the curricular part of the Master's with a classification of 15.

In September 2005 I was admitted to the Doctoral programme in Economics at FEP and since then I've completed the curricular part of the programme with a classification of 16 and prepared the present thesis on the field of Health Economics.

My interest for the Health Economics field is mainly due to my following professional position, at the Portuguese Health Regulation Authority. Since January 2006 up to the present day I've been at the Authority, where my work has been much diversified but mainly centred in research activities on the themes of access to health care, discrimination of patients and competition policy. Since 2006 I also teach Macroeconomic Policy and International Finance in undergraduate courses at the Institute of Financial and Fiscal High Studies (IESF) in Vila Nova de Gaia, Portugal.

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Finally, I must acknowledge the support of the Portuguese Health Regulation Authority, where I've been given the privilege, since 2006, to participate in the shaping of the health sector in Portugal, a task that definitely played an important role for my academic achievements.

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PREFACE

This thesis, submitted in fulfilment for the degree of Doctor of Economics, is centred in the field of Health Economics. The scope of Health Economics is considerably large, ranging from the study of the functioning of healthcare systems to individual and social causes of health affecting behaviours. However, some specific topics are currently arising as particularly important, capturing not only the interest of many researchers, but also policy makers and actors of the healthcare sector.

One of such topics concerns hospital performance in terms of cost containment and compliance with regulatory norms regarding the legal rights and legitimate interests of patients, especially when such hospitals are undergoing important reforms in terms of payment systems or management objectives. In fact, since the 1980s, several countries have been introducing financial incentives and management performance objectives in the relationship between funders and providers of healthcare (public and private). Such mechanisms, were thought to induce efficient management behaviour, in order to achieve better resource allocation, and in most cases, to contain the escalation of costs with the health system. However, many of these mechanisms designed to encourage efficiency comprise simultaneously and implicitly, some compensation for the selection of patients with lower expected treatment costs (creaming) and the rejection of patients with higher costs (dumping), and a perverse incentive for reduction of service costs through cutbacks in quality of the services provided, in ways not observable by consumers (moral hazard on the supply side).

Another important topic of Health Economics, with growing relevance, is the study of access to healthcare. Because access to healthcare is a central policy objective in most health systems, there is the need to adopt a conceptual definition of access, which allows the formulation of policies to promote access to healthcare and the monitoring of the results of these policies. In many health systems access is a concept more political than operational, lacking a comprehensive definition that comprises all components of access. For this reason, policy measures tend to be heterogeneous, uncoordinated and

sometimes contradictory. On the other hand, systems based on different access concepts are hardly comparable in terms of performance.

Additionally, promoting equitable access to healthcare is also increasingly one of the main objectives of most health systems. A common interpretation of equity leads us to the concept of horizontal equity, according to which equal medical care should be provided to individuals with equal needs. The corollary of this definition is that equity requires the provision of care to be based on the needs of populations, and not on the basis of area of residence, wealth or income, race or age of populations. The most frequently studied healthcare disparities, and more immediately associated with the concept of equity, are those that derive from the socio-economic status of individuals. More recently a distinct body of literature has arisen, focusing on disparities in care received by different ethnic and racial groups, and less frequently, on differences in healthcare utilization and type of care based on sex and age of individuals.

In face of these facts, we chose to focus our research activities in the topics of hospital performance, specifically public hospitals undergoing management reforms, equity of healthcare received by patients with different sex and age, and the concept and measures of access to healthcare.

The thesis is composed of three independent essays on such central topics of theoretical and empirical work in the field of Health Economics, as mentioned above.

In the first essay, we study the impacts of the introduction of corporatized management in Portuguese National Health Service hospitals in terms of cost, quality of services and access. We do this by comparing hospitals that were transformed into public for-profit corporations and hospitals that remained in the traditional public service format, in terms of the evolution of selected indicators over a period of nine years.

The second essay addresses the theme of discrimination of patients on the basis of gender and age. We analyze the impact of sex and age of patients in the probability of receiving intensive treatment for Acute Myocardial Infarction (AMI) within Portuguese National Health Service hospitals. Based on a theoretical model that explains health care disparities through the arguments of taste-based discrimination and statistical

discrimination, we also present an empirical test of statistical discrimination as the underlying mechanism for the discrimination of women in terms of treatment for AMI.

In the third essay we analyze small area variation in hospitalization rates for Ambulatory Care Sensitive Condition (ACSC), which are commonly described as medical conditions for which timely and appropriate outpatient care can help reduce the risk of hospitalization. With a framework that allows us to explicitly address and describe barriers faced by patients when accessing services, we conducted an empirical application examines data of hospitalizations in public hospitals and characteristics of the public primary care delivery system in small areas of Portugal in 2007.

ESSAY 1

The Corporatization of NHS Hospitals in Portugal: Cost Containment, Moral Hazard and Selection

Abstract

We study the impacts of the introduction of corporatized management in Portuguese National Health Service hospitals in twelve selected indicators of cost, quality and access to inpatient care, over a period of nine years, comparing hospitals that were transformed into public for-profit corporations (SA hospitals) and hospitals that remained in the traditional public service format (SPA hospitals). Exploration of panel data allowed us to take into account the starting position of hospitals, focusing the study on the identification of the specific effects of the conversion of hospital management. Our results point to globally positive impacts associated with the management change, not supporting the premise that the introduction of profit and performance targets in public hospitals has adverse effects of reduced quality and decreased access. On the other hand, there seems to be some evidence that supports the theory that the coexistence of hospitals with and without profit orientation results in both having similar styles of practice because the non-profit hospitals establish standards of conduct that for-profit hospitals follow.

The Corporatization of NHS Hospitals in Portugal: Cost Containment, Moral Hazard and Selection

César Alberto dos Santos Carneiro
cesar.carneiro@portugalmail.pt

1. Introduction

Since the 1980s, several countries have been introducing financial incentives and management performance objectives in the relationship between funders and providers of health care (public and private). Mechanisms such as the prospective payment system or capitation payment system for hospital production, and assessments of compliance with management objectives by hospital managers, were thought to induce efficient management behaviour, in order to achieve better resource allocation, and in most cases, to contain the escalation of costs with the health system.

However, many of these mechanisms designed to encourage efficiency, by promoting the search for good financial results, comprise simultaneously and implicitly, some compensation for the selection of patients with lower expected treatment costs (creaming) and the rejection of patients with higher costs (dumping), and a perverse incentive for reduction of service costs through cutbacks in quality of the services provided, in ways not observable by consumers (moral hazard on the supply side).

In Portugal, the shift in the management of public national health service (NHS) hospitals, from the traditional bureaucratic management of public services (Sector Público Administrativo – SPA) to for-profit management of publicly held enterprises (Sociedade Anónima – SA), aimed at introducing a package of incentives for efficiency in hospital management. Potential gains of such shift and potential negative effects in terms of patient selection and quality skimping have not been fully quantified. Thus, rigorous analytical work is needed to make a concise evaluation of the goodness of the transformation.

The aim of this work is to measure the impacts of the change in the management of NHS hospitals (from SPA to SA) on hospital costs, access and quality of services

provided. The analysis is based on data from inpatient production of a set of 58 NHS hospitals, over a period of nine years (1998 to 2006), a panel that includes hospitals which remained SPA during the analysis period (control group), and hospitals that were transformed into SA during this period. With this information, taking the hospital as the unit of analysis, we estimated the impacts of the introduction of SA management in cost and efficiency indicators (cost per patient, cost per day and average length of stay in hospital), access indicators (case-mix index and admission rate of patients with “social case” diagnosis) and indicators of quality in terms of processes (percentage of caesarean sections in total deliveries, rate of utilization of intensive methods in the treatment of acute myocardial infarction and rate of cholecystectomies by laparoscopic surgery) and in terms of outcomes (incidence of decubitus ulcers as secondary diagnosis, incidence of complications related to surgical procedures, total mortality rate and mortality rate in patients with acute myocardial infarction). The use of panel data allows us to mitigate potential issues of bias in the selection of hospitals that were transformed into SA, as well as to control for specific characteristics of each hospital.

From the results of the analysis we conclude that there are observable impacts associated with the change of hospital management type, impacts that can be considered globally positive. On for-profit public hospitals, the average cost of an inpatient episode is lower, and the average length of stay by patients on inpatient care is also significantly lower. Most indicators of outcomes show improvements in hospitals with SA management, and we didn't found evidence of changes in the case-mix of hospitals that can be attributed to this management shift. We also conclude that SA hospitals use intensive forms of treatment for acute myocardial infarction more often and perform fewer births by caesarean section. Less positive is the fact that SA hospitals decrease the admission of patients with a diagnosis of “social case”. Some of the impacts found are only statistically significant in the first year of for-profit management, suggesting a catching up effect by hospitals that remained with SPA management to a performance similar to that of SA hospitals.

These results do not seem to support the premise that the introduction of profit and performance targets in management of public hospitals has adverse effects of reduced quality and decreased access. On the other hand, the modest impacts noticed in some of

the indicators after a brief period of greater differences, seem to sustain the theory that the coexistence of hospitals with and without focus on profit leads to both having similar styles of practice, since the non-profit hospitals establish standards of conduct that for-profit hospitals follow.

This work is organized as follows: in section 2 we review some important literature on the impacts of efficiency incentives in the hospital sector; in section 3 we describe the institutional change in the management of Portuguese NHS hospitals from SPA to SA; section 4 presents the methodology of the empirical analysis carried out, from the variables to the estimation methods; the sources of all information used and the construction of the sample are detailed in section 5; a graphical and differential analysis of raw data is made in section 6; in section 7 we present the results of the statistical analysis; and section 8 closes with the discussion of the results, merits and limitations of this study.

2. Literature review

Beyond conventional intuition, several researchers have theorized and demonstrated empirically that health care providers do not have incentives for reducing (or at least controlling) their costs when they know that the funder fully reimburses them proportionally to the resources spent (Newhouse, 1970; Feldstein, 1971; Evans, 1974; Ellis and McGuire, 1986; Weisbrod, 1991). As Frank and Lave (1989) noticed, the variety of mechanisms introduced to control hospital costs include regulating hospital expenditures in capital, increasing competition in markets, increasing consumer participation in the payment of costs and changing how hospitals are paid.

In order to create incentives to reduce costs, prospective payment systems were implemented, in which providers receive a fixed amount per patient treated with a particular pathology (or group of diseases), regardless of the actual costs that result from the treatment of patients. This form of payment for hospital production induces greater efficiency in the allocation of resources in hospitals, as shown by Ellis and McGuire (1986, 1993), or Ma (1994). However, in a context of information asymmetry,

such payment systems comprise perverse incentives. Given the pressure imposed by financial incentives, hospitals can achieve cost reductions in forms that are not based in efficiency gains, such as reducing the quality of care, reducing the intensity of care (i.e., reducing the amount of resources devoted to each patient), rejecting patients with higher expected treatment costs (patient selection) or disinvesting in areas that are likely to attract patients with greater intrinsic financial risk¹ (Freiman et al., 1989; Hodgkin and McGuire, 1994; Ma, 1994; Ellis and McGuire, 1996).

The transition from cost reimbursement to prospective payment in the Portuguese NHS hospital sector begun in 1981. The effects of this transition on the performance of public hospitals, between 1984 and 1994, were studied in Lima (2000). The author concluded that the introduction of a prospective component in the hospital payment scheme contributed to significant reductions in costs per patient admitted. Lima (2000) analyzes the efficiencies of this transition but does not address the problem of quality/intensity reduction in services and patient selection.

Some less numerous and more recent studies analyze specifically how the type of ownership and management influences hospital performance. Most of this work is based on comparison of measures of efficiency, quality and access, between hospitals with and without profit objectives. Empirical evidence on this topic isn't clear. Some studies show that, on average, for-profit hospitals have a lower performance in terms of quality of care than non-profit hospitals and provide less access to users with higher treatment costs or users with less financial capacity (Gowrisankaran and Town, 1999; McClellan and Staiger, 2000; Silverman and Skinner, 2001).

However, other researchers conclude that differences between hospitals with and without profit objectives in terms of costs, quality and access are barely noticeable (Marsteller, Bovbjerg and Nichols, 1998; Sloan, 2000). Marsteller, Bovbjerg and

¹ Patient selection can arise in a context of heterogeneity of patients in terms of severity of illness. Patients with a higher degree of severity are those which are expected to have more expensive treatments, compared to the average patient. When the expected cost of treating a patient exceeds the contracted payment, the provider has the incentive not to treat that patient, or reduce the quality (and cost) of care provided. Ellis (1998) notes, however, that this argument only applies to differences in severity of illness that are not reflected in the payment system, but that the provider can observe. This situation is likely in a scenario in which the provider has more information on the degree of severity and expected costs of patients than the payer.

Nichols (1998) suggest that the similarities between hospitals with and without profit orientation may arise because non-profit hospitals establish standards of conduct that for-profit hospitals follow to some extent. Duggan (2000) concludes that the type of ownership of a hospital influences its response to opportunities to make profit, and that the distinction between public and private seems more relevant than between for-profit and non-profit, since smooth financial constraints for public hospitals reduce the impact of financial incentives.

Other studies specifically try to identify the effects of the conversion of hospitals at the level of management or ownership type. Picone et al. (2002), for example, find evidence that the conversion of public hospitals and non-profit private hospitals into profit-oriented hospitals reduces the quality of patient care, at least temporarily. Comparing hospital behaviour before and after changes in the type of management or ownership, Sloan (2000) concludes that the occurrence of the change itself is more important than the type of change.

In Portugal, the public hospital sector reform towards a profit oriented management consisted, in practice, in the introduction of incentives for efficiency of management of hospitals. To assess the experience of creation of SA hospitals in terms of efficiency, equity, access and quality, the Portuguese Government created the Commission for the Evaluation of SA Hospitals (CAHSA) in 2006. Generically, this Commission concluded that SA hospitals achieved efficiency improvements, without reducing the levels of quality and access to care. However, they also pointed out deficiencies and practical limitations to the incentives in such hospitals, for example, in terms of human resources management, treasury management, or the application of efficiency gains.

The issue of selection in Portuguese NHS hospitals was studied in Cabral (2005). The author analyzed the practices of patient admission in NHS hospitals, within a period preceding the introduction of SA management, evidencing the differences between central, district, level-1, university and oncology hospitals, in terms of severity and complexity of admitted patients.

Costa and Lopes (2005), based on information from discharge records of a set of NHS hospitals in the period of 2000 to 2004, computed clinical performance indicators for a

group of SA hospitals and a group of SPA hospitals. They concluded that after two years of maturity, the shift towards profit oriented management hadn't contributed to a decrease in access to health care. However, the conclusions were drawn without an analysis of the significance of changes over time and of differences between SA and SPA hospitals. Giraldes (2007) computed an aggregate index of efficiency, based on management indicators such as cost per user in different hospital production areas, and a quality aggregate index, based on the percentage of ambulatory surgeries in total surgeries, the rate of caesarean sections in total deliveries, the rate of autopsies and the incidence of surgical infections in surgical procedures. The author points out that publicly held corporative hospitals occupy better position than SPA hospitals in terms of the ordering of hospitals on the aggregate efficiency index. This study also lacks, however, an analysis of significance of the differences between the two groups of hospitals. Moreira (2008) evaluated the impacts of the corporatization of NHS hospitals on technical efficiency, without considering quality or access indicators. Using non-parametric methods, the author analyzed SA and SPA hospitals in the period of 2001 to 2005, concluding that SA hospitals had statistically significant efficiency gains vis-à-vis SPA hospitals, although of modest amplitude. Finally, Afonso and Fernandes (2008), also with non-parametric methods, estimated technical efficiency measures for 68 hospitals during the period of 2000 to 2005. Also in this study little attention is devoted to the differences between SA and SPA hospitals.

3. The corporatization of NHS hospitals

In Portugal, the corporatization of NHS hospitals begun in December 2002 when 31 public hospitals were taken from under the direct administration of the Government and transformed in profit-oriented corporations, with the aim of organizing the delivery of care subject to cost control and efficiency in the allocation of resources.

Corporatized (SA) hospitals remain public property (100% owned by the state), but differ fundamentally from SPA hospitals in terms of management instruments at its disposal. These hospitals acquire administrative and financial autonomy, have professionalized and independent boards of directors, accountable to the Ministry of

Health through predetermined operational and financial contracted objectives, and have freedom to hire human resources under private labour contracts.

The administrative and financial separation from its main funder (the State, through the NHS) is put in practice with funding being attributed through contracts between the Ministry of Health and each hospital. In such contracts, the NHS and the hospital agree on quantities and types of services, based on the actual production of each hospital per line of production and estimated needs for the population, and agree on the prospective payment for the overall contracted production. This logic is opposite to the traditional model of global budget with total reimbursement of costs, and constitutes an important feature – although not the only one – of the public hospital sector reform.²

These changes aimed at creating incentives and provide NHS hospitals with the means to have a more efficient management. However, the degree of autonomy and independence provided by this new type of management in public hospitals, justifies that the evaluation of this policy measure be centred on the theoretical proposition that the introduction of incentives for efficiency and improved financial performance may simultaneously lead to perverse effects of reduced quality and intensity of services provided (moral hazard by the provider), or the selection of most profitable patients.

4. Empirical analysis

4.1. Dependent variables

Cost and efficiency

In order to assess the effects on the costs of inpatient activity, we defined two indicators: cost per hospitalized patient and cost per inpatient day, both in euro deflated for 2000 with the public expenditure deflator. The impact of the management change on these indicators gives us an indication of the effects of SA management in terms of cost efficiency. Lima (2000) similarly uses these two indicators as hospital performance measures in terms of cost containment. Giraldes (2007) also includes the cost per user in

² The celebration of such contracts was expanded to SPA hospitals in 2005.

different hospital production lines (inpatient care, emergency department, ambulatory treatments and outpatient consultations) in an aggregate efficiency index.

With concern to efficiency of hospitals, we also analyzed the impact in the average length of stay (ALOS). Though not a direct measure of cost, the ALOS gives us an indication of resource usage, and therefore, it is widely used as a proxy for technical efficiency (Brownell and Roos, 1995; Martin and Smith, 1996; Lima, 2000; Kroch et al., 2007).

This variable has also been used by several researchers as a proxy for the intensity of services provided (level of resources devoted to each inpatient case), where declines in ALOS were interpreted as indicating quality skimping (Penchansky and Thomas, 1981; Guterman and Dobson, 1986; Hadley et al., 1987, 1989; Frank and Lave, 1989; Freiman et al., 1989). However, more recent literature favours the interpretation of declines in ALOS as representing gains in efficiency. Such changes in the length of stay may signify improved ability of hospitals to stabilize patients more quickly, or a trend toward discharging patients earlier and caring for them in outpatient, home, and other non-hospital settings, which would be consistent with more efficient care (Kroch et al., 2007).

In fact, as Cutler et al. (2000) point out, reducing length of stay has been a widely targeted goal for managed care utilization review in the United States (U.S.). According to Black and Pearson (2002), the English NHS responded to rising numbers of hospital admissions and delays in access to care by promoting reductions in the ALOS for each admission. These reductions were achieved by increased use of day surgery and the recognition that earlier discharge in many conditions was not dangerous and may often be better for the patient. Kroch et al. (2007) advocate that reducing the ALOS by increasing the occupancy rate in hospitals would enable the turnover rate to increase and would extend hospital benefits to a greater number of people to benefit from hospital services.

More importantly, we must note that reducing the ALOS of admissions was defined by the Portuguese Ministry of Health as one of the targets for SA hospitals, being included in contracts as a performance indicator in terms of efficiency of services.

Quality

To assess the effect of moral hazard, we analyzed indicators of quality in terms of processes and outcomes.

Quality in processes or procedures is related to the choices regarding methods/regimes of treatment, when these are not entirely dictated by purely clinical reasons. To measure quality in processes, we computed three indicators: the proportion of caesarean sections in total deliveries, the rate of utilization of “intensive” procedures for the treatment of acute myocardial infarction and the rate of cholecystectomies performed by laparoscopic surgery.

According to the World Health Organization (WHO), high rates of births by caesarean section are an element of concern because they increase the potential for complications for the mother and the newborn (WHO, 2006).³ Whenever there is not a clinical indication to the contrary, normal births (vaginal births, or eutocia) are considered preferable to caesarean section (dystocia) because they are associated with less risk of complications (since caesarean section is a surgery). However, the choice of type of delivery can be influenced by other factors of non-clinical nature. In addition to the preferences of each mother, there are factors related to the care provider, such as insufficient technical and human capacity to assist the normal delivery, hospital structure unfavourable for monitoring of labour and a greater knowledge of the caesarean surgery technique (de Regt et al., 1986; Mould et al., 1996; Roberts et al., 2000) that may induce the choice for the surgical approach. In fact, a normal childbirth is generally considered a more intensive process than the caesarean section (Gruber et al., 1999; Altman et al., 2003). As such, a more reduced percentage of caesarean sections in total deliveries is often interpreted as an indicator of increased quality in

³ There are immediate complications associated with caesarean section, such as bleeding, accidental lacerations, puerperal infections, pulmonary embolism, paralytic ileus, adverse reactions to the anesthesia, longer and more painful recovery and difficulties in breastfeeding. In the long run, the caesarean section is associated with sexual dysfunction problems and depression, and can have a negative effect on future pregnancies.

health care.⁴ CAHSA (2006) and Giraldes (2007) use this indicator with similar interpretation to assess the quality of Portuguese NHS hospitals.⁵

As explained in Cutler et al. (1998, 2000), the treatment of acute myocardial infarction (AMI) can generally be divided into two broad categories: treatment with invasive techniques and medical treatment without invasive techniques. These two blocks of treatment for AMI include the following treatment options, from the most to the least intensive: cardiac catheterization⁶ followed by coronary artery bypass graft (CABG) surgery⁷, cardiac catheterization followed by percutaneous transluminal coronary angioplasty (PTCA)⁸, catheterization without any other invasive procedure and a set of other non-invasive procedures (medication, monitoring, ...). Following the methodology of Altman et al. (2003), we have grouped CABG and PTCA procedures as “intensive” treatment options, and simple cardiac catheterization and other non-invasive treatments as “non-intensive” options. As so, the indicator of quality in processes we computed is the proportion of AMI admissions who have received intensive treatment.

Finally, also as an indicator of quality in terms of processes, we analyzed the impacts of the shift in hospital management on the laparoscopic cholecystectomy rate. Cholecystectomy is the surgical removal of the gallbladder. It is the most common method for treating patients suffering from cholecystitis (infection and inflammation of the gallbladder) or cholelithiasis (gallstones). There are two possible treatments to remove the gallbladder: “open cholecystectomy” and “laparoscopic cholecystectomy”. Laparoscopic cholecystectomy is a less invasive treatment performed through small incisions, whereas open cholecystectomy is a more invasive treatment performed through a single large incision (Siciliani, 2006). Since laparoscopic cholecystectomy

⁴ We only considered deliveries resulting in live births, since these concern, in principle, to episodes of pregnancy with lower incidence of complications. Such complications may impose greater clinical restrictions to the choice of type delivery.

⁵ The WHO has recommended since 1985 that the rate of caesarean sections not exceed 10–15%, since this is the percentage of caesareans justified by medical reasons. In every hospital and in every year in our sample, the caesarean section rate is above 15%. Thus, considering this reference rate as the optimal rate, any decline towards this reference level must be, in aggregate terms, interpreted as a welfare gain.

⁶ Cardiac catheterization is an invasive diagnostic procedure in which a contrast fluid is injected into the arteries of the patient to determine the location and size of blocking.

⁷ Coronary artery bypass graft surgery consists of replacing the blocked artery segment by a non-affected artery segment of another location in the body.

⁸ The angioplasty procedure consists of inflating a small balloon inside the affected artery in order to cause its dilatation, and consequently, unblocking it.

causes less pain, quicker healing, improved cosmetic results, shorter hospital stay and lower probability of death, when compared to open cholecystectomy, it is considered a better quality process (Gadacz, 1991). Thus, we computed this indicator as the number of laparoscopic cholecystectomy procedures on total number of discharges with cholecystectomy procedure (laparoscopic and open). Following the Agency for Healthcare Research and Quality (AHRQ)⁹ definition, we considered only discharges with age 18 years and older, and also only uncomplicated cases, and excluded cases with diagnose group 14 (pregnancy, childbirth, and puerperium).

To assess the impacts of SA management in terms of quality in outcomes, we used the hospital total mortality rate, the incidence of decubitus ulcers as secondary diagnosis, the incidence of complications after surgical procedures and the mortality rate in patients who suffered AMI.

Hospital total mortality rate was defined as the proportion of admissions registered with “deceased” as the destination after discharge, and its interpretation as a quality indicator is straight forward.

Decubitus ulcers (or pressure ulcers) are lesions resulting from an inadequate blood flow, which arise in areas where the skin has been pressed during a large period of time, by a bed or wheelchair, for example. Its appearance during hospitalization is often interpreted as a result of less attentive care on behalf of the nursing staff, failing to assist patient repositioning and inspection of susceptible areas of the skin. Hence, the incidence of decubitus ulcers is usually interpreted as a result of lower quality care (Sooda et al., 2008; Needleman et al., 2005; Kaestner and Guardo, 2008).

The incidence rate of complications after surgical procedures relates to inpatient episodes with surgery as the main procedure, which had one of the following secondary diagnosis: postoperative infection, postoperative haemorrhage or hematoma, disruption of operation wound, accidental puncture or laceration during a procedure and foreign body accidentally left during a procedure. Other alternative ways to define what can be

⁹ The AHRQ is the health services research arm of the U.S. Department of Health and Human Services, charged with improving the quality, safety, efficiency and effectiveness of health care. The agency defines quality indicators to measure various aspects of health care quality based on hospital inpatient administrative data.

included in the indicator of “surgical complications” can be found in Costa and Lopes (2005), CAHSA (2006) or Giraldes (2007).

Finally, we analyzed the mortality rate specifically in patients with diagnosis of AMI, as an indicator of quality in outcomes. As studies show, appropriate treatment of AMI can substantially reduce 30-day mortality. Furthermore, AMI is considered a condition for which the quality of care provided by the hospital has a significant impact on patient health outcomes (McClellan and Staiger, 1999). Thus, the mortality in AMI patients is widely used as an indicator of quality of health care in terms of outcomes (Krumholz et al., 1999; Shen, 2003). We computed it as the incidence of discharges coded as “deceased” on cases with AMI as principal diagnosis. We excluded from the numerator and denominator of this ratio records of incomplete admissions, i.e., admissions that were transferred to another hospital, and also cases with diagnose group 14 (pregnancy, childbirth, and puerperium).

Access

To assess the selection effect, we analyzed two indicators: the case-mix index and admissions with a diagnosis of “social case”.

The degree of complexity of patients admitted to hospitals can be used as an indicator of patient selection behaviours on behalf of health care providers, to the extent that patients with higher degree of complexity will, in principle, require greater expenditure of resources for treatment. Thus, given a fixed payment scheme (or at least, with some fixed component), such patients will represent greater financial risk to hospitals (Altman, 1990; Gilman, 2000). In this study, because the econometric analysis is done at the hospital level, we used an indicator that synthesizes the average degree of complexity of patients admitted to hospitals, the case-mix index (CMI).^{10 11}

¹⁰ The Central Administration of the Health System (ACSS) defines the CMI as a weighting coefficient of hospital production which reflects the relativity of a hospital vis-à-vis others, in terms of the complexity of its cases, computed as the ratio between the number of patients of each DRG, weighted by their relative weights, and the total number of hospital patients (Circular Normativa n.º 2 de 16 de Fevereiro de 2007, <http://www.acss.min-saude.pt/>).

¹¹ The phenomenon of selection has two dimensions that can occur simultaneously or not, but that reflect two behaviours with the same objective. One is the attraction of patients with lower degrees of severity (thus, with lower expected treatment costs) within each DRG. The second type of behaviour is the

Another access indicator we computed is the incidence of inpatient episodes with diagnoses of the category “housing, household, and economic circumstances”¹², i.e. admissions that are not justified by clinical or health related reasons. This category of diagnostic is rarely the diagnosis of admission (the main diagnostic, which justifies the admission), rather appearing most of the times as a secondary diagnosis. Since we seek to quantify how often hospitals keep patients in hospital only for what can be termed “social reasons”, we only consider patients who had diagnoses of this category as the last of the secondary registered diagnosis, reducing the probability of counting patients who, in addition to the social situation, had a medical condition that justified the continuation of inpatient care. The hypothesis tested with this indicator is that in SA hospitals, the incidence of inpatient episodes with diagnoses of this category (which for simplicity we call “social cases”) will be smaller than in SPA hospitals, since the provision of such services deviates from the strict health care scope of hospitals towards a role of social service, which might affect negatively the financial performance of hospitals. In fact, from the theoretical point of view, this type of social service is associated with non-profit providers. On this subject, Marsteller, Bovbjerg and Nichols (1998) found evidence that non-profit hospitals provide more care to disfavoured people when compared to for-profit hospitals.

The tables in Appendix summarize the description of all indicators, as well as all independent variables described below.

rejection of less profitable patients, more or less explicitly (dumping of patients). In this case, we also distinguish two possible types of rejection: vertical dumping – limiting access to patients of higher severity within patients with the same pathology; horizontal dumping – limiting admission of patients diagnosed with pathologies which have a high degree of uncertainty and therefore involve greater financial risk (in case of risk-averse agents). In this study, we infer the global selection effect from the observed degree of complexity in hospitals, which does not allow us all to distinguish partial effects of cream-skimming, vertical and horizontal dumping.

¹² This diagnostic category includes situations such as lack of accommodation, inadequate housing and individuals living alone.

4.2. Control variables

Demand side

In order to isolate the impact of management change in the defined indicators from other effects, we introduced a set of control variables for the demand conditions. Empirical studies at the patient level use patient characteristics (sex, race, age, degree of education) as a means of controlling conditions of demand and health care utilization by each patient. Since this study has the hospital as the unit of analysis, such control is carried out with aggregate variables that represent the aggregate demand profile in each hospital.

In the models used to estimate the effects of SA management in terms of costs and quality of care, we considered the CMI for each hospital as an explanatory variable, in order to purge from the estimation of other coefficients the effect of the degree of complexity of patients. Newhouse and Byrne (1988) had shown that the evidence of reduced intensity of care can be the result of misinterpreting changes in length of stay by patients. According to the authors, the observed reduction in length of stay, supposedly in response to the introduction of a prospective payment system, was not confirmed if they controlled the analysis for changes in the mix of patients. Hospitals paid prospectively had a reduction in the average length of stay because they reduced the admission of patients with pathologies that require more prolonged hospitalizations. Also Ellis and McGuire (1996) report that the indicators which aim at capturing moral hazard effects are simultaneously influenced by patient selection behaviour. Such argument can also be transposed to the case of unitary costs of treatment. Thus, we controlled potential effects of patient selection in cost and quality indicators with the independent variable CMI.

In order to control for the ability of individuals to pay for health care, we used an index of average purchasing power in the reference area of each hospital.¹³

¹³ In a health system almost entirely free of charge for users at the point of provision, as in Portugal, the influence of purchasing power on the demand for care is probably reduced. However, there might be some opportunity cost and preferences effects depending on purchasing power that should be considered.

To control for the amount and type of health care needs of populations, we considered the age distribution of patients for each hospital/year (using the proportions of individuals aged 0 to 14, 15 and 24, 25 to 64 and over 65)¹⁴, and also the mortality rates of the population in the areas of influence of hospitals, in thousands.

For variables for which data from the actual patients of hospitals wasn't available, we resorted to aggregate characteristics of the populations of the geographical area of influence of each hospital, having been defined as relevant geographical unit the municipality. In some studies on the Portuguese hospital sector (for example, Lima, 2000), the aggregate characterization of supply refers to a broader geographical unit, the district. However, we have reasons to believe that the district is an excessively broad area spanning several disparate realities, and therefore chose to confine the geographical scope of each hospital to the municipality level.¹⁵

Supply side

On the supply side, there are also some factors that can influence the performance of hospitals in terms of costs, access and quality of care, which are not directly connected to the type of hospital management, and that, consequently, must also be controlled in our study.

One of them is the size of hospitals, which allows us to control for potential economies of scale. Thus, we use number of beds (including cradles of neonatology and paediatrics) available and equipped for immediate admission of patients, as an indicator of the size of the hospital.

Another factor that we controlled is the type of hospital, which can be central, district and level-1, through dummy variables. This legal classification of NHS hospitals reflects the number of specialties that each hospital is prepared to deal with, being this number higher in central and smaller level-1 hospitals. As such, this provides us with an

¹⁴ Due to collinearity issues, we used only three variables, for ages 0 to 14, 15 to 24 and 25 to 64.

¹⁵ Note that in a study published in its *website*, ("Avaliação do Modelo de Celebração de Convenções pelo SNS") the Portuguese Health Regulation Authority concluded that for a variety of types of health care, approximately 80% of clients reside within 25 kilometers to health facilities, by which the use of the municipality as the regional unit for monitoring geographical specificities should allow properly to capture the relevant aggregate conditions of demand of each hospital.

indication of the type of production, particularly in terms of qualification of human resources and available technology at each hospital.

Also with a dummy variable, we controlled if the hospital is a university hospital, since the scope of university hospitals has additional educational objectives compared to non-university hospitals, which can have an impact on how production is organized.

The exploration of individual and time dimensions with the use of panel data allows us to control the effect of other non-observed factors, assuming that any omitted variables are time invariant. To do so, we estimated models with an unobserved individual-specific component (also called individual unobserved heterogeneity).

This is an aggregate form of controlling a series of characteristics that can affect the performance of hospitals, namely style of clinical practice. As Baumgardner (1994) and Ellis and McGuire (1996) point, doctors and hospitals often have systematic patterns of behaviour, which is called clinical practice style, that distinguishes them as providers. Most of the times, practice style cannot be captured by the observed characteristics of demand and supply, but may have an important influence on performance of providers.

Time effect

Finally, we monitored the effects of the passage of time, affecting all hospitals in the analysis, which are fixed effects by definition. This control was done through a set of dummies that identify the year of each observation.

4.3. Introduction of SA management

The shift from SPA to SA is a qualitative change in the management of NHS hospitals, and therefore a dummy variable is the adequate way to capture its effects on each of the defined indicators.

As opposed to a cross-section analysis comparing hospitals with different forms of management, focusing on the conversion of hospitals has the advantage of allowing us

to control for other relevant features, such as location of hospitals, providing a more precise identification of the effects of the type of management (Picone et al., 2002).

As we mentioned earlier, SA management consists in the introduction of a set of changes to how the hospital is managed, in terms of incentives to reduce costs and improve productive efficiency, aligning the objectives of managers with those of the NHS. Therefore, a dummy variable will capture the impact of the introduction of this set of incentives as a whole, rather than the individual effect of each characteristic of SA management.

These changes happen formally when the respective legislation is enacted, which in all cases in our sample, occurred at the beginning of a calendar year. As such, and since all indicators studied relate to calendar years of the activity of hospitals, the used dummy indicates whether in a given calendar year a particular hospital had SPA or SA management. However, it is natural that the effective implementation of new methods of management occurs gradually over time. Therefore, the period of one year may not be enough for all the effects of the change to emerge. Thus, we have introduced in our models a set of dummy variables reflecting the maturity of SA management in each hospital (variables are noted in the following tables by G1, G2 and G3, respectively taking the value 1 if it's the first, second or third or more years of SA management, and take all the value 0 when the hospital has SPA management).

4.4. Econometric model

We conducted an econometric analysis of the relationship between the binary variables that capture the shift to SA and each of the indicators of performance, controlling the considered supply and demand factors, and the effects of time. We estimated an equation for each of the 12 indicators of cost, quality and access, with the following form:

$$I_{it} = \alpha_i + \beta.D_{it} + \phi.S_{it} + \theta.A_t + \delta^1.G1_{it} + \delta^2.G2_{it} + \delta^3.G3_{it} + \varepsilon_{it}$$

In these equations, each hospital is indexed by i and each year is indexed by t . D_{it} represents the vector of variables that reflect the characteristics of demand for hospital i in year t . In the case of the equations for access indicators, the vector D_{it} differs from other equations by not including the variable CMI, which is itself an indicator of access/selection. S_{it} represents the vector of supply variables of hospital i in year t , and A_t is a set of dummy variables that identify the year. Finally, $G1_{it}$, $G2_{it}$ and $G3_{it}$ are the independent variables whose effects on the indicators interest us most, since respectively these dummies assume the value 1 if hospital i in year t is on the first, second or third year of SA management, and assume all the value 0 when the hospital has SPA management. Finally, in each equation I_{it} represents the value that the studied indicator takes in hospital i and year t .

α_i is the time invariant unobserved component, that captures the specific effect of each individual (in this case, each hospital); ε_{it} is the idiosyncratic disturbance in the econometric model, assumed with independent and identical distribution, and not correlated with D_{it} , S_{it} , A_t , $G1_{it}$, $G2_{it}$, $G3_{it}$ and α_i .

If we assume that the unobserved individual component is uncorrelated with all explanatory variables, i.e. $\text{cov}(X, \alpha_i) = 0$ (where X is any variable on vectors D_{it} , S_{it} , A_t , $G1_{it}$, $G2_{it}$ or $G3_{it}$), this means we have a random effects model. Alternatively, if we relax this assumption and let $\text{cov}(X, \alpha_i) \neq 0$ for any X , we have a fixed effects model.

Since we didn't have information that allows us to discern which of these assumptions better reflects the structure of the analyzed data, we conducted the estimation of the base-line model for all indicators with random and fixed effects estimators. Also considering the hypothesis that there is no unobserved individual-specific effect, we estimated also models by pooled OLS, an estimation procedure that does not account for any hospital-specific effects other than those already captured by the control variables in D_{it} and S_{it} .

We compared the robustness of the different estimation approaches with specific tests.¹⁶ We computed Hausman tests of the null hypothesis that the unobserved individual-specific component α_i is uncorrelated with the regressors¹⁷, based on the comparison of estimates from the fixed and random effects models. We also computed Breusch-Pagan Lagrange Multiplier (LM) tests, where the null hypothesis is that the variance of the unobserved individual-specific component α_i is null, i.e., testing the pooled OLS model against the random effects model.¹⁸

Subsequently, we analyzed in detail the results of the most robust model for each indicator.

5. Sample

The study uses aggregate data on inpatient production and costs of 58 NHS hospitals (in the case of the variables ‘rate of caesarean sections’, ‘complications after surgery’, ‘treatment of AMI’, ‘laparoscopic cholecystectomy rate’ and ‘AMI mortality rate’, the number of hospitals in the sample is 39, 56, 47, 55 and 48, respectively), patient level data that was aggregated to compute indicators at the hospital level, and socio-demographic data of municipalities where hospitals are located. Our data set covers the period from 1998 to 2006, being each of the equations estimated with a balanced panel.

The sample includes both hospitals that in this period were transformed into SA, and hospitals that at the end of the period were still SPA. We excluded from the sample oncology hospitals, psychiatric hospitals, paediatric hospitals, and other specialized hospitals (orthopaedic, infectious diseases, ...), because specialization might influence hospitals performance consistently.

¹⁶ Beck and Katz (2004) advised that, given the technical advantages and disadvantages of the several panel data estimators, we must recur to the theory to decide which model is best suited to a particular data set. When this is not possible, we should test different formalizations, on the assumption that if the tests do not give a strong indication of the existence of an unobserved specific effect, it is always preferable to use pooled OLS.

¹⁷ In practice, not rejecting the null hypothesis in the Hausman test means that estimates of random effects are preferable to those of fixed effects, because they are consistent and more efficient.

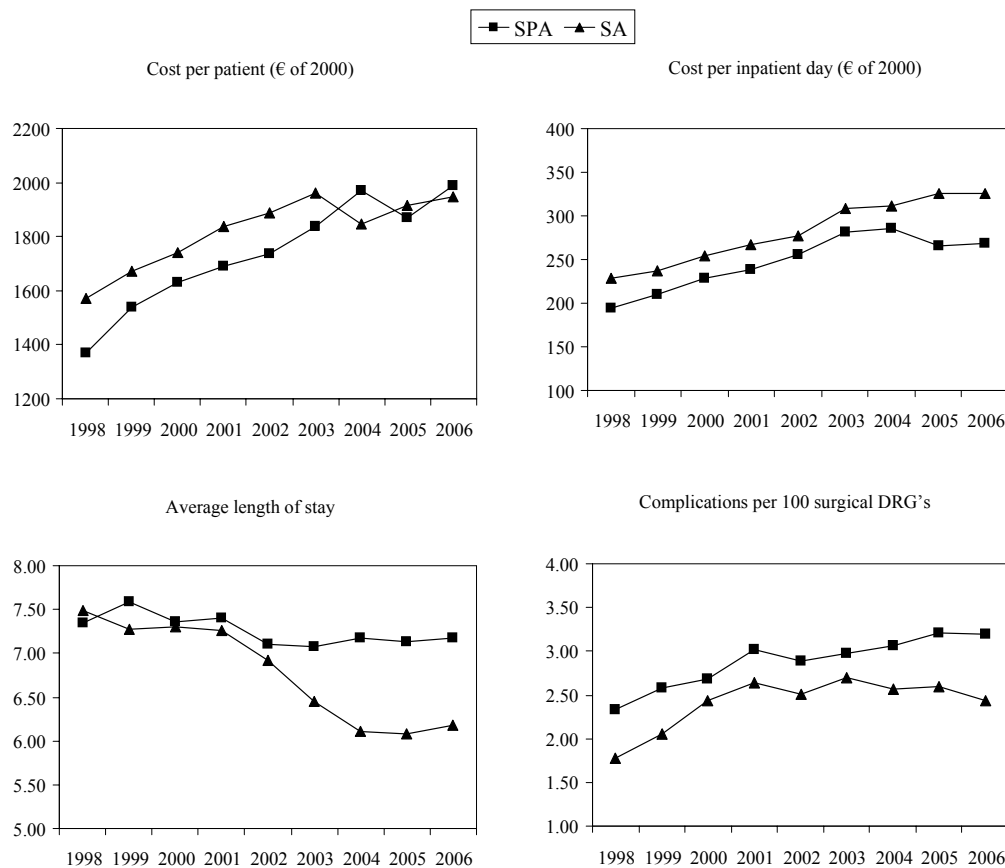
¹⁸ Rejecting the null hypothesis in the LM test means that random effects is preferable to pooled OLS, because we are rejecting the absence of an unobserved specific effect, as pooled OLS assumes.

We use various sources of information: Institute of Health Informatics and Financial Management, Directorate General of Health, Secretary General of the Ministry of Health and National Institute of Statistics.

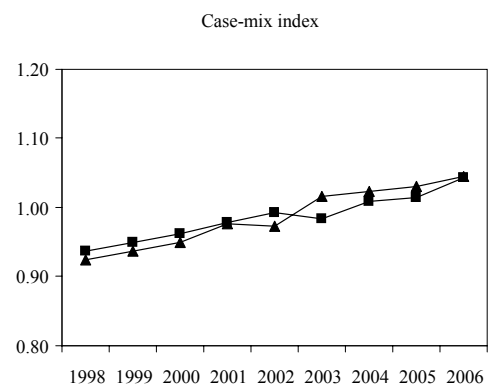
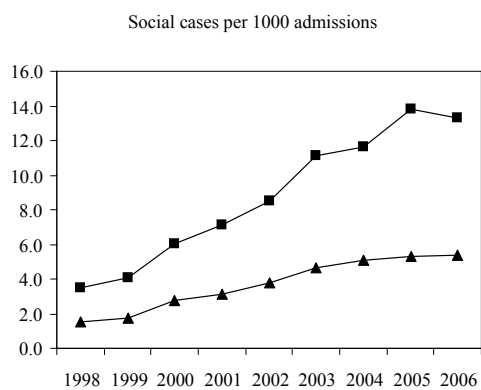
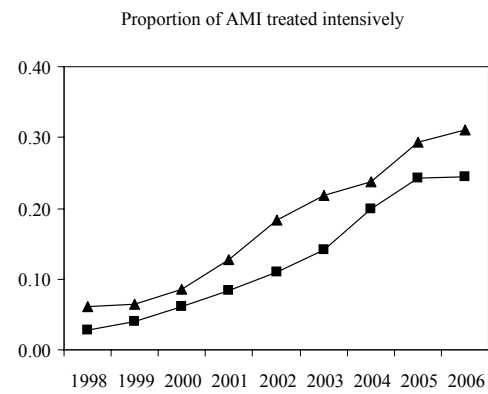
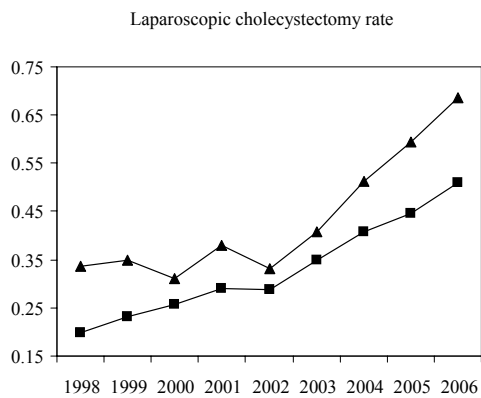
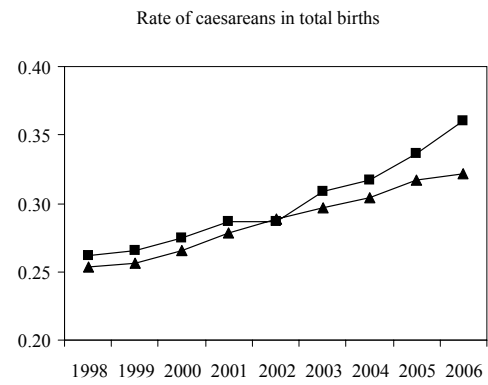
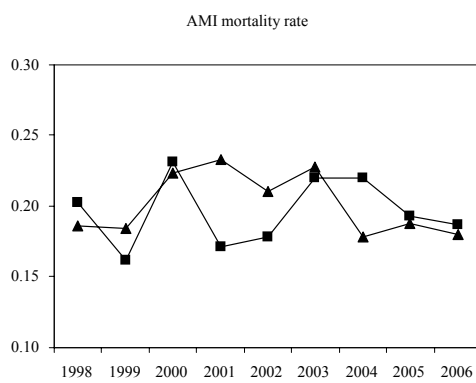
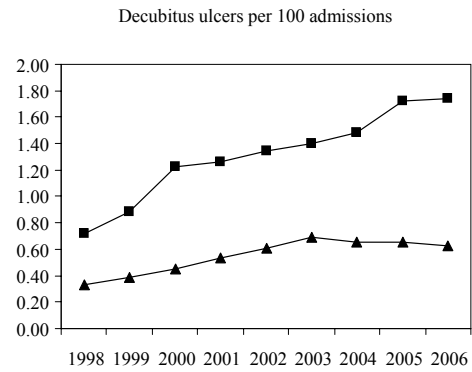
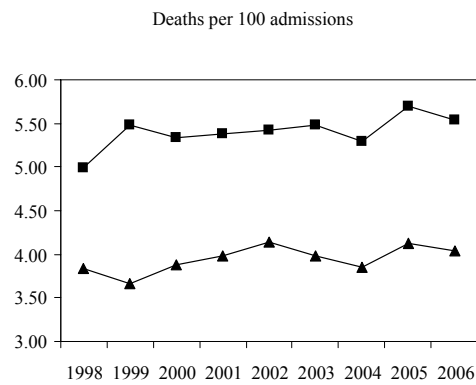
6. Summary description of the effects of SA management

The graphs in Figure 1 represent the average evolution in each of the analyzed indicators in the period of 1998 to 2006 for two groups of hospitals: a group of 34 hospitals with SPA management that keep this management throughout the period (in the graph, the SPA group), and a group of 19 hospitals with SPA management until 2002 and SA management from 2003 onwards (2003 included).¹⁹

Figure 1: Average evolution of indicators in SA and SPA hospitals



¹⁹ In order to make the graphical analysis useful, the group of SA hospitals is only composed of hospitals that shifted management type in the same year. Additionally, since in this analysis there is no control of supply and demand conditions, both groups are composed of hospitals that were similar in terms of size and costs before the transformation.



The graphs for total mortality, AMI mortality and CMI do not show relevant differences between the two groups of hospitals in terms of the evolution of the indicators.

Until 2003 the two groups of hospitals had a very similar evolution in terms of the rate of complications in surgical procedures, but in the period 2004-2006 the rate fell in SA hospitals (at an average rate of 3.38% per year), and continued to climb in SPA hospitals (at an average rate of 2.33% per year). A similar trend can be seen in the incidence of decubitus ulcers: a decline at an average rate of 3.38% per year in SA hospitals between 2004 and 2006 and a growth at 7.74% per year in SPA hospitals.

The use of intensive procedures to treat AMI has been growing in all NHS hospitals, with a slightly faster growth in the group of SA hospitals in the years 2002 and 2003, increasing the gap to the average of the SPA group, a gap that suffered a reduction in 2004 and 2005. We also observe a slight difference in the evolution of the rate of caesareans between the two groups of hospitals from 2003 to 2006: this rate has grown faster in SPA hospitals every year, at an annual average rate of 5.95% in that period, which compares to a growth of 2.73% per year in SA hospitals. The raw data shows that the rate of laparoscopic cholecystectomy has also risen slightly faster in SA hospitals than in SPA hospitals from 2003 on.

The incidence of patients kept in the hospital due to social reasons has been growing faster in SPA hospitals, although this pattern is visible already since 1999.

The average length of stay is the indicator for which the graphical illustration shows the most differentiated evolution starting in the moment of the change in management, with the corporatized hospitals having a faster decline, particularly felt in the first year of the new type of management (around 7%). The growth trend in average cost per admission is interrupted only in 2004 in SA hospitals, and a year later in SPA hospitals. The cost per day grows throughout all the analysis period in the group of hospitals that shifted to SA, and shows a drop in 2005 in SPA hospitals.

A better description of the evolution of the indicators in the two groups of hospitals can be done with a difference-in-differences analysis. This analysis consists of calculating the difference between the two groups of hospitals in two moments of time (the first

moment before the change of management in the SA group, and the second moment after this change), and subsequently calculating the difference between these differences.²⁰ Notwithstanding the limitations of not controlling for explanatory variables that can influence performance indicators, this difference-in-differences analysis is an interesting first approach to raw data, insofar as it allows us to have a general view of the dynamics of the indicators in the time period, taking into account the initial differences between the two groups of hospitals.

Table 1: Difference-in-difference analysis

Cost per patient (€ of 2000)				Cost per inpatient day (€ of 2000)			
	1998	2006	Time Diff.		1998	2006	Time Diff.
SPA	1369.83	1987.54	617.71	SPA	194.03	268.61	74.58
SA	1571.26	1948.67	377.41	SA	228.12	325.23	97.11
Group Diff.	201.43	-38.87	-240.30	Group Diff.	34.09	56.62	22.53

Average length of stay				Complications per 100 surgical DRG's			
	1998	2006	Time Diff.		1998	2006	Time Diff.
SPA	7.35	7.17	-0.18	SPA	2.33	3.19	0.86
SA	7.49	6.18	-1.31	SA	1.78	2.43	0.66
Group Diff.	0.14	-0.99	-1.14	Group Diff.	-0.56	-0.76	-0.20

Decubitus ulcers per 100 admissions				Deaths per 100 admissions			
	1998	2006	Time Diff.		1998	2006	Time Diff.
SPA	0.71	1.74	1.03	SPA	4.99	5.54	0.54
SA	0.34	0.62	0.29	SA	3.84	4.04	0.20
Group Diff.	-0.38	-1.12	-0.74	Group Diff.	-1.15	-1.49	-0.34

AMI mortality rate				Rate of caesareans in total births			
	1998	2006	Time Diff.		1998	2006	Time Diff.
SPA	0.20	0.19	-0.02	SPA	0.26	0.36	0.10
SA	0.19	0.18	-0.01	SA	0.25	0.32	0.07
Group Diff.	-0.02	-0.01	0.01	Group Diff.	-0.01	-0.04	-0.03

Proportion of AMI treated intensively				Laparoscopic cholecystectomy rate			
	1998	2006	Time Diff.		1998	2006	Time Diff.
SPA	0.03	0.24	0.22	SPA	0.20	0.51	0.31
SA	0.06	0.31	0.25	SA	0.34	0.69	0.35
Group Diff.	0.03	0.07	0.03	Group Diff.	0.14	0.18	0.04

²⁰ Since all hospitals in the SA group suffered the shift in management in 2003, we defined 1998 as the “before” moment and 2006 as the “after” moment.

Case-mix index				Social cases per 1000 admissions			
	1998	2006	Time Diff.		1998	2006	Time Diff.
SPA	0.94	1.04	0.10	SPA	3.51	13.30	9.79
SA	0.93	1.04	0.12	SA	1.49	5.35	3.86
Group Diff.	-0.01	0.00	0.01	Group Diff.	-2.01	-7.95	-5.93

It should be noted that the group of hospitals that were transformed into SA presented better results in outcome quality indicators (in this case, lower rates of complications, ulcers, total deaths and AMI deaths) already in 1998, and that this position is reinforced until 2005 (except for AMI death). Differences in quality in processes seem less relevant, although also in favour of SA hospitals. The steeper reduction on average length of stay observed in these hospitals is again highlighted, as well as in the proportion of admissions with “social case” diagnosis. The cost per day has higher growth in the SA group during the period, but the cost per patient has a more modest growth.

In summary, this analysis signals that the corporatization of NHS hospitals might have had the following average effects: improvement in indicators of quality in terms of outcomes and reduced impact on the choices of intensive treatment processes; decrease in the incidence of “social case” admissions and virtually nil impact in *case-mix* index; decrease in the average length of stay, decrease in the cost per admitted patient and increase in the cost per day. Hence, these preliminary conclusions do not seem to support the premise that the introduction of profit and management performance targets in public hospitals results in adverse effects of reduced quality and decreased access.

After this preliminary assessment, we looked at how much of the evolution in indicators of quality, access and cost is attributable to the change of management from SPA to SA, controlling other factors that may have an impact on the performance of hospitals, in particular variables that configure the supply and demand for each hospital.

7. Results

For each of the defined indicators we estimated three regressions: one with unobserved individual effects based on the random effects estimator, another based on the fixed

effects estimator, and yet another by pooled OLS. The following tables present the results of all regressions. The bottom rows of the tables contain general information about the quality of the adjustment of the models and the results of tests computed to choose the most appropriate model, while at the top we present the estimates of coefficients and standard deviations of the binary variables for the shift to SA management, and also the coefficients of the control variables, with the exception of year dummies.

Cost containment and efficiency effect

The results of the regressions on the variable cost per patient are presented in Table 2.

In the LM test we reject the hypothesis that the variance of the unobserved individual effect is null, which means that the random effects estimation is preferable to OLS. Additionally, in the Hausman test we do not have evidence to reject the null hypothesis of the coefficients of random effects and fixed effects models not being significantly different. Thus, in this case the random effects estimator is preferable because it is consistent and more efficient than the fixed effects estimator.²¹ On the basis of the tests carried out, we found that the most appropriate model to the data is the random effects model, which presents an overall R^2 of about 0.77 and is globally statistically significant.

The estimated coefficient of dummy variable G1 is not significantly different from zero, which means that after one year of SA management there weren't visible effects on this indicator. The estimated coefficient of G2 has statistical significance (at 1%) and negative sign, indicating that after two years of SA management there was a reduction in the average cost per admitted patient in these hospitals, vis-à-vis the ones that remained SPA, of about 244 euros. However, this differential decreases in the third year, in such a way that it becomes statistically irrelevant even at a significance level of 10%.

With the exception of the number of beds, mortality rate and university dummy, control variables present statistical relevance at least to a significance level of 10%.

²¹ Note that the fixed effects estimator is always consistent, regardless of whether or not there is correlation between unobserved effects and the observed explanatory variables.

Table 2: Regression results of cost per patient

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	9.9197 (82.0494)	56.9802 (68.8967)	65.9171 (69.9228)
G2it	-299.4440 *** (95.2150)	-243.6296 *** (80.2897)	-232.0530 *** (81.5999)
G3it	-129.9027 * (68.5916)	-64.9462 (61.1964)	-48.7837 (62.8141)
<i>Control variables</i>			
Bedsit	0.1568 (0.1028)	0.1090 (0.1892)	0.2404 (0.3621)
Centralit	422.6053 *** (93.7065)	563.9293 *** (171.8012)	- -
Districtit	113.5392 ** (49.2850)	155.0490 * (94.5303)	- -
Universityit	-265.9625 ** (113.3619)	-246.9565 (223.6209)	- -
CMItit	1367.3800 *** (118.5017)	1306.6580 *** (154.7468)	1109.1750 *** (203.1938)
PPIit	1.5532 *** (0.4657)	1.7506 *** (0.6837)	0.7403 (0.9859)
Mortit	37.8010 *** (9.6156)	22.0400 (15.0768)	2.0689 (25.3934)
Age1it	148.9750 (279.5602)	-727.8761 * (427.7146)	-1541.4180 ** (641.8307)
Age2it	2714.5440 *** (1106.2240)	4592.0670 *** (1401.6090)	5370.0930 *** (1635.3560)
Age3it	205.7275 (315.8601)	-768.1761 * (406.4907)	-1633.3720 *** (518.6141)
<i>No. of observations</i>			
<i>Prob>F / Prob>chi2</i>			
<i>Adjusted R2</i>			
<i>"Overall" R2</i>			
<i>"Between" R2</i>			
<i>"Within" R2</i>			
<i>LM test (Prob>chi2)</i>			
<i>Hausman Test (Prob>chi2)</i>			

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

In the case of cost per inpatient day, LM and Hausman tests indicate that the most appropriate model is also the random effects. The estimated coefficients indicate that the cost per day is greater with SA management, but the gap has only statistical

relevance in the third year of SA management. This differential amounts to approximately 24 euros, an increase of 9.7% compared to the average cost per day in hospitals prior to the shift to SA.

Table 3: Regression results of cost per day

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	13.0465 (18.0687)	4.7568 (14.0734)	1.6342 (14.1814)
G2it	12.0892 (20.9679)	3.2716 (16.4048)	0.5562 (16.5497)
G3it	39.1758 *** (15.1050)	24.3921 ** (12.5405)	19.4413 (12.7397)
<i>Control variables</i>			
Bedsit	-0.0573 *** (0.0226)	-0.0890 ** (0.0431)	-0.1692 ** (0.0734)
Centralit	16.1467 (20.6357)	52.0590 (39.7003)	- -
Districtit	-0.7037 (10.8534)	8.2862 (22.0330)	- -
Universityit	74.4482 *** (24.9642)	92.4387 * (52.3273)	- -
CMIit	105.3142 *** (26.0961)	101.9151 *** (33.0694)	96.9416 ** (41.2108)
PPIit	0.6317 *** (0.1025)	0.2051 (0.1487)	-0.0179 (0.2000)
Mortit	-1.2508 (2.1175)	6.4408 * (3.3341)	8.4716 * (5.1502)
Age1it	158.6536 *** (61.5638)	178.3390 * (93.8144)	174.2824 (130.1730)
Age2it	377.9192 (243.6091)	895.4049 *** (296.1833)	1157.3990 *** (331.6749)
Age3it	-271.1734 *** (69.5577)	-104.2052 (86.7118)	-18.9998 (105.1828)
<i>No. of observations</i>			
	522	522	522
<i>Prob>F / Prob>chi2</i>			
	0.0000	0.0000	0.0000
<i>Adjusted R2</i>			
	0.4151	-	-
<i>"Overall" R2</i>			
	-	0.3975	0.0442
<i>"Between" R2</i>			
	-	0.4508	0.0004
<i>"Within" R2</i>			
	-	0.3145	0.3220
<i>LM test (Prob>chi2)</i>			
	-	0.0000	-
<i>Hausman Test (Prob>chi2)</i>			
	-	-	0.5288

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

On the other hand, there is a relevant decrease – of 7.4%, after three years – in the average length of stay in SA hospitals. If we interpret this indicator as a proxy of the quantity of resources needed to treat patients, this decrease indicates productive efficiency gains attributable to SA hospitals (table 4).

Table 4: Regression results of ALOS

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	-0.5007 (0.4087)	-0.1274 (0.2594)	-0.0577 (0.2555)
G2it	-1.1232 ** (0.4743)	-0.6924 ** (0.3025)	-0.6301 ** (0.2982)
G3it	-1.1236 *** (0.3417)	-0.5204 ** (0.2321)	-0.4215 * (0.2295)
<i>Control variables</i>			
Bedsit	0.0017 *** (0.0005)	0.0028 *** (0.0010)	0.0050 *** (0.0013)
Centralit	0.8621 * (0.4668)	1.0491 (0.9371)	- -
Districtit	0.3422 (0.2455)	0.0628 (0.5287)	- -
Universityit	-2.8632 *** (0.5647)	-4.0094 *** (1.2593)	- -
CMItit	3.1106 *** (0.5903)	1.9876 *** (0.6557)	1.0871 (0.7425)
PPIit	-0.0117 *** (0.0023)	0.0016 (0.0030)	0.0005 (0.0036)
Mortit	0.1663 *** (0.0479)	-0.1245 * (0.0705)	-0.2483 *** (0.0928)
Age1it	-4.0887 *** (1.3926)	-10.3677 *** (1.9416)	-10.7804 *** (2.3455)
Age2it	-0.4446 (5.5103)	4.9992 (5.7225)	5.7202 (5.9762)
Age3it	8.0672 *** (1.5734)	-2.2270 (1.7124)	-5.2013 *** (1.8952)
<i>No. of observations</i>			
522			
<i>Prob>F / Prob>chi2</i>			
0.0000			
<i>Adjusted R2</i>			
0.4430			
<i>"Overall" R2</i>			
-			
<i>"Between" R2</i>			
-			
<i>"Within" R2</i>			
-			
<i>LM test (Prob>chi2)</i>			
-			
<i>Hausman Test (Prob>chi2)</i>			
-			

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

Moral hazard effect

In the case of all 7 quality indicators, the most appropriate model, according to tests performed, is the random effects.

Concerning quality in terms of outcomes, most estimated coefficients of the variables indicating SA management have negative sign, revealing a trend of improved performance in hospitals that shifted from SPA to SA. The exception is AMI mortality. However, for the variable surgical complications per 100 admissions with surgical DRG, number of deaths per 100 admissions and number of deaths per patient diagnosed with AMI, estimates have no statistical relevance to a significance level of 10%. Only in the case of incidence of decubitus ulcers, the differential attributable to the change from SA to SPA management is statistically significant, after three years. This increase of the differential (which before the change was already favourable to hospitals that came to be transformed in SA) represents a reduction of approximately 72% of the average incidence during the previous period.

Table 5: Regression results for surgical complications

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	-0.3021 (0.3105)	0.0525 (0.2506)	0.0662 (0.2481)
G2it	-0.6912 * (0.3607)	-0.3226 * (0.1922)	-0.2630 (0.2894)
G3it	-0.5731 ** (0.2618)	-0.1403 (0.2246)	-0.1009 (0.2241)
<i>Control variables</i>			
Bedsit	0.0009 ** (0.0004)	0.0001 (0.0007)	-0.0014 (0.0013)
Centralit	1.0486 *** (0.3586)	2.5570 *** (0.6788)	- -
Districtit	0.7838 *** (0.1893)	0.9977 *** (0.3694)	- -
Universityit	-0.1306 (0.4257)	0.3088 (0.8660)	- -
CMIit	2.7133 *** (0.4627)	0.6848 (0.6007)	-1.5612 ** (0.7424)
PPIit	0.0001 (0.0019)	-0.0024 (0.0026)	-0.0101 *** (0.0036)
Mortit	-0.0571 (0.0371)	-0.0363 (0.0572)	-0.1018 (0.0900)
Age1it	-4.2767 *** (1.1116)	-4.5881 *** (1.6526)	-2.1538 (2.3251)
Age2it	2.6907 (4.4729)	-7.0699 (5.6906)	-11.7875 * (6.4318)
Age3it	-9.7760 *** (1.4694)	-9.3532 *** (1.7094)	-10.5814 *** (1.9219)
<i>No. of observations</i>			
504			
<i>Prob>F / Prob>chi2</i>			
0.0000			
<i>Adjusted R2</i>			
0.3813			
<i>"Overall" R2</i>			
-			
<i>"Between" R2</i>			
-			
<i>"Within" R2</i>			
-			
<i>LM test (Prob>chi2)</i>			
-			
<i>Hausman Test (Prob>chi2)</i>			
-			

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

Table 6: Regression results of decubitus ulcers

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	-0.1563 (0.1958)	-0.0990 (0.1222)	-0.0921 (0.1235)
G2it	-0.2019 (0.2272)	-0.2247 (0.1424)	-0.2180 (0.1441)
G3it	-0.3134 * (0.1636)	-0.3326 *** (0.1093)	-0.3337 *** (0.1109)
<i>Control variables</i>			
Bedsit	-0.0006 ** (0.0002)	-0.0008 * (0.0005)	-0.0009 (0.0006)
Centralit	-0.0435 (0.2236)	0.0596 (0.4585)	- -
Districtit	-0.4866 *** (0.1176)	-0.5844 ** (0.2593)	- -
Universityit	0.4124 (0.2705)	0.4494 (0.6174)	- -
CMItit	-0.4465 (0.2827)	-0.2757 (0.3117)	-0.3832 (0.3588)
PPIit	0.0015 (0.0011)	0.0016 (0.0014)	0.0014 (0.0017)
Mortit	-0.0833 *** (0.0229)	-0.0542 * (0.0338)	-0.0182 (0.0448)
Age1it	-4.1135 *** (0.6670)	-3.7745 *** (0.9278)	-3.5446 *** (1.1334)
Age2it	-13.3841 *** (2.6392)	-9.3428 *** (2.7088)	-9.0679 *** (2.8880)
Age3it	-5.1543 *** (0.7536)	-7.4017 *** (0.8133)	-8.1172 *** (0.9159)
<i>No. of observations</i>			
522			
<i>Prob>F / Prob>chi2</i>			
0.0000			
<i>Adjusted R2</i>			
0.5105			
<i>"Overall" R2</i>			
-			
<i>"Between" R2</i>			
-			
<i>"Within" R2</i>			
-			
<i>LM test (Prob>chi2)</i>			
-			
<i>Hausman Test (Prob>chi2)</i>			
-			

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

Table 7: Regression results of total mortality

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	-0.6517 * (0.3776)	-0.0670 (0.1901)	-0.0210 (0.1892)
G2it	-0.5879 (0.4382)	-0.0589 (0.2217)	-0.0011 (0.2208)
G3it	-0.6118 ** (0.3157)	-0.0193 (0.1704)	0.0255 (0.1700)
<i>Control variables</i>			
Bedsit	-0.0011 ** (0.0005)	0.0002 (0.0008)	0.0011 (0.0010)
Centralit	1.3964 *** (0.4312)	1.2964 (0.8854)	- -
Districtit	0.1229 (0.2268)	0.0352 (0.5065)	- -
Universityit	-1.2538 ** (0.5217)	-2.5939 ** (1.1996)	- -
CMItit	0.9292 * (0.5454)	-0.3623 (0.5065)	-0.3569 (0.5498)
PPIit	-0.0018 (0.0021)	0.0082 *** (0.0024)	0.0096 *** (0.0027)
Mortit	0.1603 *** (0.0443)	0.1492 *** (0.0574)	0.2282 *** (0.0687)
Age1it	-3.9956 *** (1.2866)	-10.5863 *** (1.5431)	-12.4145 *** (1.7367)
Age2it	-29.6468 *** (5.0910)	-25.4168 *** (4.3083)	-25.7256 *** (4.4251)
Age3it	-3.5099 ** (1.4536)	-9.0935 *** (1.3160)	-10.3192 *** (1.4033)
No. of observations	522	522	522
Prob>F / Prob>chi2	0.0000	0.0000	0.0000
Adjusted R2	0.4921	-	-
"Overall" R2	-	0.4608	0.3670
"Between" R2	-	0.4876	0.3814
"Within" R2	-	0.3222	0.3256
LM test (Prob>chi2)	-	0.0000	-
Hausman Test (Prob>chi2)	-	-	0.6109

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

Table 8: Regression results of AMI mortality

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	0.0714 * (0.0380)	0.0364 (0.0344)	0.0161 (0.0350)
G2it	0.0259 (0.0447)	-0.0228 (0.0405)	-0.0500 (0.0411)
G3it	0.0546 * (0.0326)	0.0022 (0.0312)	-0.0249 (0.0323)
<i>Control variables</i>			
Bedsit	-0.0001 (0.0000)	-0.0001 (0.0001)	-0.0001 (0.0002)
Centralit	-0.0380 (0.0442)	-0.0406 (0.0726)	- -
Districtit	-0.0766 *** (0.0250)	-0.0667 (0.0419)	- -
Universityit	0.0605 (0.0523)	0.0618 (0.0899)	- -
CMlit	-0.0188 (0.0582)	-0.0631 (0.0751)	-0.1211 (0.1060)
PPlit	0.0004 * (0.0002)	0.0004 (0.0003)	0.0004 (0.0005)
Mortit	-0.0042 (0.0054)	-0.0050 (0.0077)	-0.0151 (0.0140)
Age1it	-0.5888 *** (0.1548)	-0.3248 (0.2149)	0.2083 (0.3453)
Age2it	2.3999 *** (0.5807)	0.6278 (0.7562)	-0.8985 (0.9947)
Age3it	-1.0317 *** (0.2308)	-0.4864 (0.2643)	-0.0627 (0.3206)
No. of observations	432	432	432
Prob>F / Prob>chi2	0.0000	0.0000	0.0000
Adjusted R2	0.1364	-	-
"Overall" R2	-	0.1094	0.0020
"Between" R2	-	0.2376	0.0001
"Within" R2	-	0.0162	0.0303
LM test (Prob>chi2)	-	0.0000	-
Hausman Test (Prob>chi2)	-	-	0.2046

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

Considering the indicators of quality in processes, we found a statistically significant reduction in the rate of births by caesarean section attributable to SA management (table 9), but only after three years and at a significance level of 10%. This reduction, of about

5.7% in the rate of caesareans considering the average rate before SA, is interpreted as welfare enhancing since the rate of caesarean sections in Portuguese NHS hospitals is consensually higher than it should. A statistically significant positive impact observed in the use of intensive forms for treatment of AMI, which represents an increase of around 69%, also after three years (table 10), is also considered a gain in quality attributable to SA management. In the case of the rate of laparoscopic cholecystectomy, the signs of the estimated coefficients in SA dummy variables also indicate quality enhancement, although the results are not statistically significant.

Table 9: Regressions results for the proportion of caesareans

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	-0.0115 (0.0163)	-0.0085 (0.0091)	-0.0061 (0.0091)
G2it	-0.0060 (0.0190)	-0.0014 (0.0106)	0.0008 (0.0105)
G3it	-0.0170 (0.0139)	-0.0152 * (0.0083)	-0.0137 * (0.0083)
<i>Control variables</i>			
Bedsit	-0.0001 *** (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Centralit	0.0077 (0.0216)	-0.0323 (0.0553)	- -
Districtit	-0.0311 ** (0.0142)	-0.0423 (0.0377)	- -
Universityit	0.1778 *** (0.0266)	0.0653 (0.0597)	- -
CMItit	-0.1211 ** (0.0572)	-0.1214 *** (0.0467)	-0.0956 ** (0.0480)
PPIit	-0.0003 ** (0.0001)	0.0002 (0.0001)	0.0003 * (0.0002)
Mortit	-0.0052 ** (0.0026)	-0.0058 * (0.0031)	-0.0033 (0.0038)
Age1it	-0.1861 * (0.1051)	-0.4665 *** (0.1202)	-0.5687 *** (0.1397)
Age2it	-0.8164 ** (0.3353)	0.3567 (0.2865)	0.5364 * (0.2958)
Age3it	0.2110 (0.1465)	0.0943 (0.1447)	0.0852 (0.1653)
No. of observations	351	351	351
Prob>F / Prob>chi2	0.0000	0.0000	0.0000
Adjusted R2	0.3556	-	-
"Overall" R2	-	0.2429	0.0534
"Between" R2	-	0.1514	0.0017
"Within" R2	-	0.4825	0.4912
LM test (Prob>chi2)	-	0.0000	-
Hausman Test (Prob>chi2)	-	-	0.2718

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

Table 10: Regressions results for intensive treatment of AMI

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	0.0358 (0.0235)	0.0363 * (0.0202)	0.0302 (0.0194)
G2it	0.0296 (0.0277)	0.0312 (0.0239)	0.0240 (0.0230)
G3it	0.0725 *** (0.0203)	0.0637 *** (0.0186)	0.0520 *** (0.0181)
<i>Control variables</i>			
Bedsit	0.0002 *** (0.0000)	0.0001 ** (0.0001)	0.0001 (0.0001)
Centralit	-0.0176 (0.0269)	0.0655 (0.0479)	- -
Districtit	0.0297 * (0.0157)	0.0454 (0.0288)	- -
Universityit	-0.0441 (0.0322)	-0.0445 (0.0613)	- -
CMIit	0.2956 *** (0.0354)	0.2728 *** (0.0464)	0.1200 ** (0.0580)
PPIit	0.0006 *** (0.0001)	0.0001 (0.0002)	-0.0010 *** (0.0003)
Mortit	0.0047 (0.0034)	0.0097 ** (0.0050)	-0.0136 * (0.0077)
Age1it	0.3192 *** (0.0948)	0.2445 * (0.1356)	0.5297 *** (0.1937)
Age2it	-0.2375 (0.3605)	0.8009 * (0.4841)	2.0458 *** (0.5722)
Age3it	0.0447 (0.1314)	0.1987 (0.1574)	0.3128 * (0.1779)
<i>No. of observations</i>			
	422	422	422
<i>Prob>F / Prob>chi2</i>			
	0.0000	0.0000	0.0000
<i>Adjusted R2</i>			
	0.7019	-	-
<i>"Overall" R2</i>			
	-	0.6900	0.0082
<i>"Between" R2</i>			
	-	0.7825	0.0430
<i>"Within" R2</i>			
	-	0.4972	0.5503
<i>LM test (Prob>chi2)</i>			
	-	0.0000	-
<i>Hausman Test (Prob>chi2)</i>			
	-	-	0.2505

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

Table 11: Regressions results for laparoscopic cholecystectomy rate

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	0.0689 (0.0657)	0.0055 (0.0411)	0.0010 (0.0413)
G2it	0.0696 (0.0767)	0.0031 (0.0482)	-0.0004 (0.0485)
G3it	0.1083 ** (0.0557)	0.0460 (0.0372)	0.0415 (0.0375)
<i>Control variables</i>			
Bedsit	0.0000 (0.0001)	0.0002 (0.0002)	0.0004 * (0.0002)
Centralit	-0.0567 (0.0753)	-0.1174 (0.1675)	- -
Districtit	-0.0350 (0.0396)	-0.0738 (0.0866)	- -
Universityit	0.0431 (0.0909)	-0.0729 (0.2131)	- -
CMIit	0.1957 * (0.1106)	0.2233 ** (0.1114)	0.1955 * (0.1216)
PPIit	0.0008 ** (0.0004)	0.0007 (0.0005)	0.0005 (0.0006)
Mortit	0.0000 (0.0078)	-0.0037 (0.0112)	0.0029 (0.0147)
Age1it	0.3328 (0.2510)	1.2675 *** (0.3245)	1.5406 *** (0.3907)
Age2it	2.1651 *** (0.9466)	-2.5664 *** (1.0052)	-3.5264 *** (1.0714)
Age3it	1.2136 *** (0.3072)	1.2542 *** (0.2963)	1.1527 *** (0.3179)
<i>No. of observations</i>			
495			
<i>Prob>F / Prob>chi2</i>			
0.0000			
<i>Adjusted R2</i>			
0.2890			
<i>"Overall" R2</i>			
-			
<i>"Between" R2</i>			
-			
<i>"Within" R2</i>			
-			
<i>LM test (Prob>chi2)</i>			
-			
<i>Hausman Test (Prob>chi2)</i>			
-			

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

Selection effect

Invariably, tests indicate that the random effects estimator is the most appropriate for the two access indicators we studied.

The results suggest a positive impact on the CMI attributable to SA management, i.e., an increase on the average degree of complexity of patients admitted to hospitals, but with some statistical relevance only in the first year (which was already visible graphically). In terms of the incidence of “social cases”, estimated coefficients indicate a statistically significant negative impact of SA management, concretely an increase of the differential in the number of “social cases” by 1000 admissions relatively to SPA hospitals, which was already unfavourable to SA before the management shift. This effect, which is statistically relevant only at the end of the third year, represents an increase of 70% in the differential.

Table 12: Regression results of CMI

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	0.0489 (0.0309)	0.0314 * (0.0169)	0.0281 * (0.0162)
G2it	0.0394 (0.0359)	0.0295 (0.0198)	0.0264 (0.0190)
G3it	0.0192 (0.0258)	0.0097 (0.0152)	0.0088 (0.0146)
<i>Control variables</i>			
Bedsit	0.0000 (0.0000)	0.0000 (0.0001)	0.0001 (0.0001)
Centralit	0.4201 *** (0.0299)	0.6083 *** (0.0681)	- -
Districtit	0.0511 *** (0.0184)	-0.0080 (0.0418)	- -
Universityit	-0.1371 *** (0.0423)	-0.2065 ** (0.0988)	- -
PPIit	0.0008 *** (0.0002)	-0.0001 (0.0002)	-0.0007 *** (0.0002)
Mortit	0.0240 *** (0.0035)	0.0221 *** (0.0049)	0.0125 ** (0.0059)
Age1it	-0.7626 *** (0.0997)	-0.4390 *** (0.1337)	-0.1327 (0.1493)
Age2it	-1.6211 *** (0.4107)	-0.4068 (0.3823)	-0.1921 (0.3806)
Age3it	1.1671 *** (0.1071)	0.2979 *** (0.1155)	0.0655 (0.1207)
<i>No. of observations</i>			
522			
<i>Prob>F / Prob>chi2</i>			
0.0000			
<i>Adjusted R2</i>			
0.8190			
<i>"Overall" R2</i>			
-			
<i>"Between" R2</i>			
-			
<i>"Within" R2</i>			
-			
<i>LM test (Prob>chi2)</i>			
-			
<i>Hausman Test (Prob>chi2)</i>			
-			

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

Table 13: Regression results of the proportion of social cases

Variable	Pooled OLS	Random effects	Fixed effects
<i>SA management</i>			
G1it	-5.7777 ** (2.7624)	-2.7933 (1.8850)	-2.2736 (1.9046)
G2it	-5.3723 * (3.2056)	-2.8226 (2.1979)	-2.4015 (2.2226)
G3it	-6.9810 *** (2.3093)	-4.4482 *** (1.6850)	-4.0434 ** (1.7109)
<i>Control variables</i>			
Bedsit	-0.0114 *** (0.0035)	-0.0112 * (0.0067)	-0.0080 (0.0099)
Centralit	4.7167 (3.1549)	4.9927 (6.3887)	- -
Districtit	4.8630 *** (1.6593)	0.7793 (3.5900)	- -
Universityit	4.7177 (3.8166)	1.1394 (8.5511)	- -
CMIit	5.1309 (3.9896)	-1.2982 (4.6863)	-6.1009 (5.5346)
PPIit	-0.0230 (0.0157)	0.0069 (0.0215)	0.0081 (0.0269)
Mortit	0.2114 (0.3237)	0.4445 (0.4960)	0.2473 (0.6917)
Age1it	9.5849 (9.4121)	16.1440 (13.7432)	35.6200 ** (17.4822)
Age2it	-128.2152 *** (37.2437)	-58.6386 (41.1786)	-36.7970 (44.5439)
Age3it	19.4896 * (10.6342)	13.4847 (12.2519)	12.6652 (14.1260)
<i>No. of observations</i>			
	522	522	522
<i>Prob>F / Prob>chi2</i>			
	0.0000	0.0000	0.0000
<i>Adjusted R2</i>			
	0.1374	-	-
<i>"Overall" R2</i>			
	-	0.1355	0.0157
<i>"Between" R2</i>			
	-	0.1263	0.0011
<i>"Within" R2</i>			
	-	0.1552	0.1613
<i>LM test (Prob>chi2)</i>			
	-	0.0000	-
<i>Hausman Test (Prob>chi2)</i>			
	-	-	0.9558

Note: Standard-deviations between parenthesis; ***Significant at 1%; **Significant at 5%; *Significant at 10%

8. Discussion

In Portugal, the creation of incentives for increased efficiency in resource allocation in public hospitals has been operated through corporatization of these hospitals, initially by transforming them into publicly held enterprises. The potential efficiency gains of such change and the potential negative effects of patient selection and quality reduction have been studied on the basis of various indicators and different methodologies. However there are still no consensus about the direction and the magnitude of these effects.

We study the impacts of the introduction of SA management in NHS hospitals in performance in terms of cost, quality of services and access, from the observation of twelve selected indicators over a period of nine years, in a group composed by hospitals that were transformed into SA and hospitals that remained in the traditional public service format. Two of these indicators were related to costs and one related to productive efficiency, four related to quality in terms of outcomes, three related to quality in terms of processes and two related to access.

Exploration of panel data allowed us to take into account the starting position of hospitals which were transformed into SA relatively to hospitals that remained SPA, focusing the study on the identification of the specific effects of the conversion of hospital management. In addition, we controlled conditions of supply and demand of each hospital over time, and not just the effect of the passage of time, as happens with the analysis of the difference-in-differences. In fact, the impacts suggested by the difference-in-differences analysis arise in our statistical procedure with overall smaller amplitude, some having no statistical significance at all, and therefore, considered null on the basis of the available data. As such, the achieved quantification is useful to understand the impacts of SA management in the three dimensions studied.

Estimation of models based on the random effects estimator proves to be more appropriate than with fixed effects estimator or simple pooled OLS to all indicators.²²

²² For the estimated equations, if the tests indicated fixed effects as the most appropriate method, the analysis of the results of estimation would be hampered. As Beck and Katz (1995) explain, even when it is the most efficient estimator, fixed effects does not deal correctly with time invariant explanatory

After three years of SA management, the level of costs per patient is negatively affected by the new type of management but only with statistically insignificant amplitude, while the cost per day presents a positive impact of approximately 9.7%. The ALOS, defined as a proxy for resource usage, presents a negative variation attributable to SA management of 7.4%, which indicates productive efficiency gains. Additionally, almost all indicators of quality in terms of outcomes show improvements attributable to SA management, although these improvements are only expressive in the case of incidence of decubitus ulcers (weaker effects are observed in the rate of surgical complications, total mortality and AMI mortality). SA hospitals also show improvements in indicators of quality in processes. We observe a decline of 5.7% in the rate of caesarean section and an increase of 69% in the rate of use of intensive forms for treatment of AMI, both attributable to SA management. Evidence on selection effects warrants a more careful interpretation. The incidence of “social cases” is an indicator of access in which we estimated a negative impact of 70% attributable to SA management. The CMI doesn't seem to be affected.

Some of the indicators with statistically irrelevant impact after three years of SA management present a relevant impact on the first year, which ends up being cancelled in the following years. The graphical illustration of the evolution of such indicators over time points to a dynamic of catching up by SPA hospitals.

Theoretically, there is reason to expect that there are relevant disparities between hospitals with a profit-oriented management and purely public non-profit hospitals in terms of efficiency, quality and access provided to users. However, in line with several other studies, the evidence analyzed suggests reduced impacts of the conversion of NHS hospitals into corporatized publicly held hospitals, and those that have statistical relevance go in the opposite direction to the hypotheses of adverse selection and moral hazard.

Our results point to globally positive impacts associated with the change in the management of NHS hospitals, not supporting the premise that the introduction of profit

variables (or with small variance, such as dummy variables), because their effects are collinear with the fixed effect of each individual.

and management performance targets in public hospitals has adverse effects of reduced quality and decreased access. On the other hand, there seems to be some evidence that supports the theory that hospitals with and without profit orientation coexisting have similar styles of practice since the non-profit hospitals shall establish standards of conduct that for-profit hospitals follow. In the present case, these standards of practice arise naturally in SA hospitals for various reasons beyond the mere coexistence with purely public hospitals: legal tying of corporatized hospitals to the NHS principles and values, common to all public establishments; social and political pressure that accompanies the hospital management reform; practice style of SA hospitals professionals shaped by a long experience serving in non-profit public hospitals.

Two final notes should be taken into consideration. First, the extraction of conclusions from the results of the analysis presented here is always conditional upon the interpretation of the defined indicators. The effects detected on indicators are, *per se*, interesting, although what they suggest is certainly subject to discussion. The interpretation considered here followed, whenever possible, relevant literature.

Second, in interpreting these results it should be noted that the data used only captures effects occurring until the year 2006, which means, for most hospitals transformed into SA, a period of implementation of the new managerial culture of four years, a period that may have been insufficient to reveal all the effects of the shift in management, either positive or negative.

Appendix

Quality, access and cost/efficiency indicators

Indicator	Definition
<u>Quality in outcomes</u>	
Surgical complications	Number of admissions classified with surgical DRG with complications related to that surgical procedure, per 100 surgical DRG
Mortality	Number of admissions with indication of “deceased” as the destination after discharge, per 100 admissions
Decubitus ulcers	Number of admissions with secondary diagnosis of decubitus ulcer, per 100 admissions
AMI mortality	Number of admissions with indication of “deceased” as the destination after discharge on total cases with AMI as principal diagnosis
<u>Quality in processes</u>	
Caesareans	Number of births by caesarean section (DRG 370 and 371) on total births
Laparoscopic cholecystectomy	Number of admissions with laparoscopic cholecystectomy procedure on total number of admissions with cholecystectomy procedure
AMI treated intensively	Number of acute myocardial infarction episodes treated with coronary artery bypass graft surgery and/or angioplasty on total number of AMI
<u>Access</u>	
Case-mix index	Case-mix index computed according to the methodology of ACSS
Social cases	Number of admissions with last secondary diagnosis from the category of “housing, household, and economic circumstances” (code V60), per 1000 admissions
<u>Cost and efficiency</u>	
Cost per day	Average cost per day of inpatient care (€ of 2000)
Cost per patient	Average cost per patient admitted (€ of 2000)
ALOS	Average length of stay in hospital, in days

Independent variables

Variable	Description
<u>SA management</u>	
G1it	=1 if for hospital i year t is its first with SA management
G2it	=1 if for hospital i year t is its second with SA management
G3it	=1 if for hospital i year t is its third or later with SA management
<u>Demand side</u>	
CMIit	case-mix index of hospital i in year t (ACSS methodology)
PPIit	average purchasing power index of municipality of hospital i in year t (reference=100)
Age1it	proportion of patients aged 0-14 in hospital i in year t
Age2it	proportion of patients aged 15-24 in hospital i in year t
Age3it	proportion of patients aged 25-64 in hospital i in year t
Mortit	mortality rate of municipality of hospital i in year t (in thousands)
<u>Supply side</u>	
Bedsit	number of beds in hospital i in year t
Centralit	=1 if hospital i is central hospital in year t
Districtit	=1 if hospital i is district hospital in year t
Universityit	=1 if hospital i is university hospital in year t
<u>Time effect</u>	
y1998	=1 if observation is relative to fiscal year 1998
y1999	=1 if observation is relative to fiscal year 1999
y2000	=1 if observation is relative to fiscal year 2000
y2001	=1 if observation is relative to fiscal year 2001
y2002	=1 if observation is relative to fiscal year 2002
y2003	=1 if observation is relative to fiscal year 2003
y2004	=1 if observation is relative to fiscal year 2004
y2005	=1 if observation is relative to fiscal year 2005

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ESSAY 2

“Ageism” and “Sexism” in Portuguese NHS Hospitals: Differences in Treatment of Patients with Acute Myocardial Infarction based on Age and Sex

Abstract

In this essay we analyze the impact of sex and age of patients in the probability of receiving intensive treatment for Acute Myocardial Infarction (AMI) within Portuguese National Health Service (NHS) hospitals. To do so, we use data from 89,026 discharge records of NHS hospitals between 2000 and 2008. After controlling for the severity of patients with a Disease Staging classification, our results suggest that older patients and females are less likely to receive an intensive treatment than younger and male patients. With a receiver operating characteristics analysis we estimate that 52% of the female patients of our sample were undertreated according to the standard of treatment applied to men, a rate that is 15 percentage points higher than in men. We also observe that undertreated women had a higher probability of death than other females not treated. Finally, we found that the magnitude of sex based discrimination in AMI treatment depends on if the hospital was subject to a corporatization shift by which financial and performance incentives were imposed to some NHS hospitals in Portugal. We interpret this as evidence compatible with statistical discrimination being one of the underlying mechanisms for the discrimination of women in terms of treatment for AMI.

“Ageism” and “Sexism” in Portuguese NHS Hospitals: Differences in Treatment of Patients with Acute Myocardial Infarction based on Age and Sex

César Carneiro
cesar.carneiro@portugalmail.pt

1. Introduction

Promoting universal and equitable access to health care is increasingly one of the main objectives of most health care systems. A common interpretation of equity leads us to the concept of horizontal equity, according to which equal medical care should be provided to individuals with equal needs (Wagstaff et al., 1991; Morris et al., 2004). The corollary of this definition is that equity requires the provision of care to be based on the needs of populations, and not on factors such as area of residence, wealth or income, race or age of populations (Wagstaff and Doorslaer, 2000).

In the literature we find references to the related concept of disparities in health care, which are defined as differences in treatment provided to members of different social groups not justified by the underlying health conditions or needs of the patient (Balsa and McGuire, 2003). There is a long tradition in the study of variations, or disparities, in the amount or type of health care received that are associated with patients' personal characteristics, such as socio-economic status, sex, race, age or ethnicity. Perhaps the most frequently studied health care disparities, and more immediately associated with the concept of equity, are those that derive from the socio-economic status of individuals. More recently, and especially in the United States, a distinct body of literature has arisen, focusing on disparities in care received by different ethnic and racial groups. Differences in health care utilization and type of care based on sex and age of individuals have also been addressed in such literature, although less frequently.

On the issue of age-based disparities, we find in the literature statistical evidence that suggests that medical care provided to older individuals is different from that provided to the younger, in terms not entirely justified by medical reasons. Such differences arise at the level of the physician/patient interaction, the use of preventive diagnostic

procedures and treatment of numerous health problems (Goodwin, 1998; Levinsky et al., 1999; Turner et al., 1999).¹

In the study of variations in access to health care and type of care based on sex, there is empirical evidence that suggests that women receive less attention from caregivers and receive less intensive treatments, when compared to men with similar diagnosis. There is also evidence suggesting that women are subject to longer waiting times than men for the same health services, and are subject to less monitoring procedures for health problems (Black et al., 1994; Chesney and Ozer, 1995; Hanratty et al., 2000; Perelman et al., 2007).

While it is common to associate these disparities to discrimination, some authors note that discrimination only happens when there are no medical reasons to justify differences in the amount and type of care received by different population groups (Kane and Kane, 2005). Additionally, recent literature in health care disparities distinguishes several possible mechanisms of discrimination responsible for disparities not supported in different health conditions or needs. These mechanisms can be grouped in two leading theories: taste-based discrimination and statistical discrimination. Taste-based discrimination refers to disparities in treatment that are caused by pure prejudice or bias² felt by doctors against members of particular social groups. Statistical discrimination in the health context refers to the situation where the doctor, facing uncertainty about the patient's severity of illness, relies on statistical evidence about the prevalence of the illness in the social group to which the patient belongs, inducing him to behave differently with otherwise identical members of different social groups (Werner, 2004; Balsa et al., 2005).

In this study we analyze the impact of sex and age of patients, along with other variables, in the probability of receiving intensive treatment of acute myocardial

¹ As Robb, Chen and Haley (2002) mention, the theme of age discrimination in the provision of health care has been a topic of discussion and research for over 30 years. The literature on the theme focuses on the concept of "ageism", a term coined by Butler (1975) as a way to highlight the similarities between age discrimination and other forms of discrimination based on race (racism) and sex (sexism). As defined by Kane and Kane (2005), "ageism" in health care refers to situations where older people are specifically disadvantaged or treated in a less than desirable way because of their age.

² Such bias is commonly termed "taste for discrimination" in the theory of discrimination originated by Becker (1971).

infarction (AMI) within Portuguese National Health Service (NHS) hospitals. To do so, we use data from 89,026 discharge records of NHS hospitals between 2000 and 2008. In our econometric procedure we control for both hospital and patient characteristics; specifically at the patient level, we conducted a Disease Staging analysis in order to control for the severity of illness of patients. This empirical analysis is preceded by a theoretical exploration, through a model of doctor choice, of two possible causes of health care disparities based in sex and age of patients: prejudice and rational profiling.

This study is organized as follows: in section 2 we present a theoretical model that explains health care disparities through the arguments of prejudice and rational profiling; in section 3 we summarize some important findings on disparities in the treatment of cardiovascular diseases; in section 4 we detail the objectives of the empirical analysis, the design of the study and the variables used, and describe the data analyzed; section 5 presents the results of the econometric estimation; in section 6 we explore some welfare implications of the disparities of treatment for AMI based on gender; in section 7 we present an empirical test of statistical discrimination as the underlying mechanism for the discrimination of women in terms of treatment for AMI; and in the eighth and last section we draw some important conclusions.

2. Theoretical model

Building mainly on the work of Balsa and McGuire (2003), we introduce in this section a simple model of doctor choice of treatment that allows us to define standards of fairness and efficiency. In their original model, race is the basis of categorization of patients. However, the theoretical framework allows us to explore the impacts, in terms of health care disparities, of any other categorization of patients based either on prejudice by doctors or on prior beliefs held by doctors facing uncertainty.

We start with the benchmark case of a benevolent doctor with perfect information and latter evolve to two alternative settings: the case where the doctor has some kind of prejudice, where we explore an argument based on the theory of discrimination originated by Becker (1971); and the case where the benevolent doctor facing clinical

uncertainty uses average information on patient groups to improve diagnosis (Balsa and McGuire, 2003).

2.1. The benchmark case: benevolent doctor with complete information

We start the model by considering the existence of two recognizable groups of patients, men and women (respectively indexed, in our notation, with M and W), considering that gender is a potential basis of categorization by doctors.³

Additionally, each patient is characterized by a severity of illness, denoted by Z . A patient with a higher value of Z is more severely ill. In this model, treatment consists of a yes/no decision made by the doctor,⁴ and the benefit a patient gets from receiving treatment is the complete elimination of the illness. More precisely, we define Z as the net benefit a patient gets from receiving treatment, i.e., the level of severity of illness minus the risk and discomfort associated with treatment. When a patient has a negative value of Z , that means that the treatment is not effective from the doctor's point of view because the patient will not benefit from it. That is the case when the patient is not sick enough to justify the treatment or he bears a risk so high that he's better off without treatment. One important assumption is that given a value of Z , gender does not matter in how a patient benefits from treatment. We also assume that there are no costs of treatment (we will relax this last assumption in the next section).

Now consider that patients of different groups may differ in the underlying distribution of severity. Thus, for men we have $Z \sim N(\mu_M, \sigma^2)$, and for women $Z \sim N(\mu_W, \sigma^2)$, which means we assume that men and women may have a different group mean severity, but the variance in the distribution of severity is the same for both groups.

Given this set of assumptions, we now analyze the doctor's decision regarding treatment. As we already mentioned, in this model the doctor has to choose to assign

³ Although the original model of Balsa and McGuire (2003) is presented with race (Blacks and Whites) as the basis of categorizations of patients, the model is generalizable to any other potentially relevant categorization of patients, such as age and gender (the topics of our study).

⁴ In our empirical application we will study a dichotomous variable that distinguishes patients with intensive treatment and non-intensive treatment. The arguments in this theoretical model can easily accommodate such decision in the same fashion as a yes/no decision.

patients to treatment or not. The doctor's strategy is to choose a threshold Z^* that determines the cut-off between patients who do and do not get treatment. At this point we must define fair and efficient choices. The resulting choices are fair if, given severity, the treatment decision does not depend on group membership. On the other hand, choices are efficient if there is no alternative rule that makes everyone at least as well off and some individuals strictly better off.

In the benchmark case, the doctor is benevolent in the choice of treatment, so given the available information, the doctor makes his treatment recommendation so as to maximize the patient's expected benefits from treatment. Also, the doctor has complete information about the patient's health needs, i.e., he is able to accurately observe the severity Z of each patient. And naturally gender is always observable.

Such a benevolent doctor with complete information about severity will assign patients to treatment if and only if the benefits of treatment to the patient are positive. Hence, only patients with $Z \geq 0$ will get treatment. Thus, the doctor will choose the threshold $Z^* = 0$ for both men and women.

The resulting allocation is fair because for any given severity, gender doesn't matter in the doctor's decision about treatment. Any man or woman with severity Z gets the same treatment assignment and outcome. Nevertheless, we may observe some disparities in the shares of men and women receiving treatment, but that doesn't constitute an unfair decision. If $\mu_w < \mu_m$, for example, fewer women will have values of $Z \geq 0$, and a smaller share of women will be treated.

The allocation is also efficient because since the doctor makes the best choice for all patients, there is no way of changing the distribution of treatment without worsening the health care outcomes of one or more patients.

2.2. Prejudice: ageism and sexism

One possible explanation for clinical disparities is that physicians hold a bias or a "prejudice" against members of some groups of patients.

We follow Becker (1971) and Balsa and McGuire (2003), and define prejudice as a distaste felt by doctors when interacting with certain groups of patients⁵, economically represented as a (psychological) exogenous cost in the objective function of the prejudiced doctor. We denote this cost as d .

Now, assume $d = 0$ for male patients and $d > 0$ for female patients. As before, benefits from treatment are given by Z , but now the doctor maximizes the patient's benefit net of this psychological cost ($Z - d$). Treatment is again a yes/no decision and the doctor's strategy is to choose a threshold Z^* that determines the cut-off between patients who do and do not get treatment.

The doctor will again assign patients to treatment if and only if the net benefits of treatment to the patient are positive. In the case of men, that happens when $Z \geq 0$, so all men with $Z \geq 0$ will be assigned to treatment. But for women, the doctor is faced with the problem $Z - d \geq 0$. Thus, only women with $Z \geq d$ will receive care. This means that the doctor will choose the threshold $Z_M^* = 0$ for male patients and $Z_W^* = d$ for female patients. Therefore, given that doctors face any positive physiological cost d when interacting with female patients, the result will be $Z_W^* > Z_M^*$, so that fewer women will be treated, and more important, for severities between Z_M^* and Z_W^* , men will be treated but not women.

This allocation is unfair because for some severity levels, female patients are receiving a different treatment recommendation than male patients with same severity. The obvious implication of this analysis is that women will be under-treated.

Whether the allocation is efficient or not depends on if the "psychological cost" experienced by the prejudiced doctors is accepted as legitimate or not. One might argue that in terms of social welfare the psychological cost faced by doctors, if it exists, must not be ignored in order to achieve an efficient allocation of treatment.

⁵ Kastenbaum (1964) described ageism primarily as a physiological cost felt by therapists when treating older patients. Based on qualitative observations, he defined the "reluctant therapist" as a health professional that absorbed cultural attitudes such as notions that old age was accompanied by diminished status, aversion to the aging process as foretelling the clinicians' own future and cultural stereotypes that portrayed joy evaporating with old age. All these were ageist criteria offered as an explanation why therapists would avoid treating older persons.

2.3. Rational profiling

A second possible source of disparity in treatment is clinical uncertainty. Physicians usually make diagnosis and treatment decisions in a context of uncertainty. Thus, they must depend on inferences about disease and severity based on symptoms that can be observed and what else the doctor observes about the patient.

Consider that doctors cannot observe disease and its severity, but can only observe signals, or symptoms, of the underlying problem. Given imperfect information about the patient's health status, doctors have to rely on "easy-to-observe" variables, such as age, gender, culture, ethnicity and other life circumstances, to improve their inference about the patient's condition. Balsa and McGuire (2003) call such behaviour "rational profiling".

In order to describe the impacts of rational profiling in our model, we must assume that the means of the underlying severity distributions differ by gender. Assume, for example, $Z \sim N(\mu_M, \sigma^2)$ for men and $Z \sim N(\mu_W, \sigma^2)$ for women, and $\mu_W < \mu_M$, i.e., women are on average healthier. Differences in mean severity are meant to capture differences in the likely benefit of therapy.

The doctor perceives these different means. However, he cannot observe Z for a particular patient, but only a symptom or signal of severity, S , such that $S = Z + \varepsilon$, where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ and distributed independent of Z . The term ε captures the noise that impedes the doctor to accurately observe the severity Z of each patient, and we consider it identical for men and women. In other words, the variance of the noise, σ_ε^2 , is a measure of the degree of uncertainty present between the doctor and the patient.

Again, the benevolent (unprejudiced) doctor seeks to maximize each patient's expected health outcome by recommending treatment only when the expected benefits of that treatment are positive.

Assume further that in face of uncertainty, the doctor uses Bayes' rule to formulate an expectation on the benefit based on the mean severity (prior information) and the observed signal (posterior information). Thus, for a patient with signal S , the expected benefit is $(1 - \beta)\mu_i + \beta S$, where $\beta = \frac{\sigma^2}{\sigma^2 + \sigma_\varepsilon^2}$ and $i \in \{M, W\}$.

The term β corresponds to a measure of the quality of the signal. When the signal is noisier (higher σ_ε^2), β is lower and the doctor will put less weight on the signal and more on the mean severity.

The doctor's strategy consists of selecting a threshold observed severity level S^* and recommending treatment to all those patients with severity high enough to exceed that threshold. Given the expected benefit, the chosen threshold will be $S_i^* = -\left(\frac{1 - \beta}{\beta}\right)\mu_i$, $i \in \{M, W\}$.

We can easily observe that if $\mu_W < \mu_M$, then $S_W^* > S_M^*$. The choice will be driven by the prior information the doctor has on the mean severity of different patient groups, since all other terms are similar across genders. The doctor will find it optimal to set a higher threshold for the group with a lower mean severity.

This outcome is unfair because gender matters in the decision. The doctor will be impelled by what is referred to as "rational profiling" to treat some males and females with the same severity differently. For observed signals of severity between S_M^* and S_W^* , men will be treated but not women.

On the other hand, the decision is efficient because the doctor makes use of all available information to make the choice that maximizes the expected benefit of every patient. Given that the doctor faces clinical uncertainty, using Bayes' rule to update priors based on patient characteristics with observed signals yields a second-best allocation.

The main conclusion we draw from this simple model of doctor choice is that disparities in treatment of people with the same level of severity based on demographic group may

appear even if there is no prejudice or bias; in face of clinical uncertainty doctors may do rational profiling of patients, a statistical discrimination mechanism that generates disparities even if the doctor is benevolent. The result is an unfair but efficient allocation of treatment.

As mentioned before, the model just described is based mainly on the work of Balsa and McGuire (2003). However, several other works conceptualize potential sources of health disparities, of which Einbinder and Schulman (2000), Balsa and McGuire (2001) and Bloche (2001) are examples. Considerably less frequent are empirical works that try to measure the magnitude and the importance of these different sources of disparities. Two of the few examples are Werner (2004) and Balsa et al. (2005). In the first of these studies, the author tests the hypothesis of taste-based discrimination against statistical discrimination as the source of racial and ethnic differences in coronary bypass use, and finds evidence consistent with the presence of statistical discrimination. In the second case, the authors find evidence consistent with statistical discrimination for diagnoses of hypertension, diabetes and depression, associated with race, age and gender.

3. Empirical evidence on disparities in the treatment of cardiovascular diseases

The case of diagnosis and treatment of cardiovascular diseases is a particularly recurrent area for the study of variations in health care based either on age or sex of patients. As noted by Bowling et al. (2001), decisions to investigate patients invasively and subsequent management decisions about the treatment of heart diseases involve issues of clinical appropriateness, but also patient's preferences, and the personal preferences and bias of the physician. In this context, variations in treatment that are statistically attributed to sex or age, *ceteris paribus*, are a sign of discrimination based on such personal characteristics.

Levinsky et al. (1999) noted that admissions for common medical procedures, such as cardiovascular procedures, decreased with increasing age of patients. There is also evidence indicating that beta-blocker based therapy for secondary prevention after acute myocardial infarction (AMI) is relatively less used in older patients. Soumerai et al.

(1997) concluded that advanced age was an important factor explaining the finding that only 21% of eligible patients received beta-blocker therapy. Additionally, Fairhead and Rothwell (2006) concluded that there was substantial underinvestigation in routine clinical practice in patients over 80 years of age with transient ischemic attack or stroke.

Evans (1997), on the theme of discrimination of older people in the English NHS, states that the best example of this phenomenon is substandard treatment of AMI and other forms of heart disease, which leads to unnecessary premature deaths and disabilities. Bowling (1999) notes that rates of potentially life-saving and life-enhancing cardiological interventions, such as revascularisation, are higher in younger groups of individuals, despite the prevalence of cardiovascular diseases is considerably higher in older groups. In this study, the older had a higher probability of suffering severe cardiovascular diseases and be treated medically and not surgically, and were less likely to receive the most effective treatment after AMI.

Several studies also report evidence suggesting that women with heart disease are treated less intensively than men. Hippisley-Cox et al. (2001) found a systematic bias in favour of men, when compared with women, in terms of secondary prevention of ischemic heart disease. The data analyzed revealed that among patients with ischemic heart disease, women were less likely than men to have their risk factors, such as body mass index, smoking habits and blood pressure, recorded. Clarke et al. (1994) had earlier found that women with myocardial infarction took longer than men to arrive in hospital, were less likely to be admitted to coronary care specialized units, and were therefore less likely to receive thrombolytic treatment. There were also differences at the time of discharge, with women being less likely to receive secondary prophylaxis based on aspirin and beta-blockers. Ayanian and Epstein (1991) also showed that women hospitalized with coronary heart disease were less often subject to diagnostic and therapeutic procedures, and Maynard et al. (1992) concluded that despite high levels of risk factors and mortality, coronary angiography and angioplasty were used less often in women.

Some of these studies consider simultaneously the age and sex of patients, in order to capture the impact of each of these factors on the amount and type of treatment received. Black et al. (1994) and Bowling et al. (2001) found evidence of less intensive

treatment of heart disease for aged and female patients. On the other hand, Williams et al. (2004) claim that the potential gender bias in terms of clinical management after AMI is not motivated by “sexism” (sex discrimination), but rather is a reflection of age of patients, since women with such diagnosis are on average older than men.

4. Empirical analysis

4.1. Objectives and study design

The aim of this study is to examine whether there is a significant association between sex and age of a patient admitted in Portuguese NHS hospitals with diagnosis of AMI and the type of treatment he or she receives. We also consider in the econometric procedure variables that characterize the hospital where the patient is treated, in order to control potential effects of practice style on the choices of type of treatment. The results of this empirical study give us an indication about which of these characteristics influence the type of treatment received by patients with AMI.

The patient is the unit of analysis. Given two alternative choices of treatment of AMI, intensive and non-intensive, we estimate the impact of a set of patient-specific and hospital-specific characteristics on the probability of a patient with this diagnosis to receive an intensive treatment.

Define $Y_{ij} = 1$ when patient i receives intensive treatment in hospital j and $Y_{ij} = 0$ when patient i receives another type of treatment (non-intensive) in hospital j . The binary choice model that tells us how the probability of a patient receiving intensive care in a given hospital is dependent on vectors $\mathbf{X}_i$ and $\mathbf{Z}_j$ of explanatory variables has the generic form $E[Y_{ij} | \mathbf{X}_i, \mathbf{Z}_j] = \Pr[Y_{ij} = 1 | \mathbf{X}_i, \mathbf{Z}_j] = F(\mathbf{X}_i' \boldsymbol{\beta}, \mathbf{Z}_j' \boldsymbol{\delta})$, where $E[\]$ is the expected value and $\Pr[\]$ is the probability.

To estimate the binary choice model we conventionally assume that $F(\cdot)$ has the functional form of a logistic distribution, which gives us the logit model.⁶ This model was estimated by maximum likelihood.

In vector $\mathbf{X}_i$ (with $i = 1, \dots, N$) of explanatory variables we considered patients' personal characteristics and in vector $\mathbf{Z}_j$ (with $j = 1, \dots, J$) we have hospital characteristics.

We used information on the treatment of patients with a diagnosis of AMI admitted in NHS hospitals in several years. However, although we used data from several individuals and several years, in fact we don't have a panel data structure, since each individual is identified only once in the data set. Even in the case where a patient has been admitted with AMI more than once in different years, the data do not allow us to keep track of that patient over time. Thus, we chose to pool the data and treat it like a cross-section, but controlling the passage of time with a set of dummy variables for years.

An additional note concerning the structure of the data is in order. Although the unit of analysis (the individual) is not repeated over time, it is likely that estimation residuals from observations of patients treated in the same hospital are correlated. This means we admit that the decision of using intensive treatment techniques may depend on the specific characteristics of each hospital, as the availability of specialized human resources and technology. We can interpret observations of patients treated in the same hospital as a group (or cluster) of observations, and the correlation among observations of the same hospital as intra-cluster correlation. In the presence of such intra-cluster correlation, logit estimates are still unbiased but straight forward standard errors may be quite wrong. Thus, to allow for inference we corrected the standard deviations with Rogers (1993) method, which assumes that there are several clusters of observations (as

⁶ In the logit model, $F(\alpha) = \Lambda(\alpha) = \frac{e^\alpha}{1 + e^\alpha}$, where $\Lambda(\cdot)$ is the logistic cumulative distribution function.

many as hospitals) and observations within each cluster are correlated with each other, but not correlated with observations from other clusters.⁷

Formalization of the Rogers (1993) robust variance/covariance estimator is presented in appendix 1.

4.2. Variables and measures

As we mentioned before, the dependent variable of our econometric model is a binary variable that takes the value 1 when the treatment received by the patient is intensive and 0 when the treatment is non-intensive. Bearing in mind that the classification of intensive and non-intensive treatments of AMI is naturally subject to alternative definitions, in the present analysis we followed important research literature on the subject.

As Cutler et al. (1998, 2000) explain, the treatment of AMI can generally be divided into two broad categories: treatment with invasive techniques and medical treatment without invasive techniques. These two blocks of treatment of AMI include the following treatment options, from the most to the least intensive: cardiac catheterization⁸ followed by coronary artery bypass graft (CABG) surgery⁹, cardiac catheterization followed by percutaneous transluminal coronary angioplasty (PTCA)¹⁰, catheterization without any other invasive procedure and a set of other non-invasive procedures (medication, monitoring, ...).

Following the methodology of Altman et al. (2003), we have grouped CABG and PTCA procedures as “intensive” treatment options, and simple cardiac catheterization and other non-invasive treatments as “non-intensive” options. Other works that follow

⁷ STATA9TM has a built-in routine to obtain Rogers (1993) robust standard error estimates adjusted for within cluster correlation. For an overview of methods for analyzing cluster-correlated data, see Fitzmaurice et al. (2004).

⁸ Cardiac catheterization is an invasive diagnostic procedure in which a contrast fluid is injected into the arteries of the patient to determine the location and size of blocking.

⁹ Coronary artery bypass graft surgery consists of replacing the blocked artery segment by a non-affected artery segment of another location in the body.

¹⁰ The angioplasty procedure consists of inflating a small balloon inside the affected artery in order to cause its dilatation, and consequently, unblocking it.

similar definition of intensive treatment of AMI are Goldberg et al. (1992) and Chen et al. (2001).

Also as already mentioned, we have two groups of explanatory variables, one reflecting patient characteristics, and the other one reflecting hospital characteristics. All variables are described in table 1.

The variable **sexi** is binary, assuming the value 1 when the patient is female, while the variable **agei** is the patient's age in years (thus, an integer value). These are the variables whose impact on the type of treatment received is of greatest interest, giving us an indication if age and sex are relevant predictors of the probability of a patient with AMI to get an intensive treatment in a NHS hospital. Still on the side of patient characteristics, we considered the binary variable **fini** that takes the value 1 when the financial responsible for the coverage of costs with the patient's treatment is the NHS, and 0 if the funder is other entity (here we include public and private health subsystems and insurance companies). Although not the central focus of this study, this variable allows us to test if the health care funder is a relevant predictor of the probability of obtaining intensive care.

Finally, in order to control for the severity of illness of patients we conducted a Disease Staging analysis of which resulted two variables: the disease stage of the patient in terms of severity, defined as the risk of organ failure or death (**stagei**), and a dummy variable that takes the value 1 if the patient was diagnosed as having had prior coronary revascularization (**cvs10i**). This Disease Staging analysis is described in detail in the next section.

Table 1: Independent variables

Notation	Description
<i>Patient</i>	
sex _i	=1 if sex of patient <i>i</i> is feminine
age _i	age of patient <i>i</i>
fin _i	=1 if financial responsible for care of patient <i>i</i> is NHS
stage _i	severity stage of disease of patient <i>i</i>
cvs10 _i	=1 if patient had prior coronary revascularization
<i>Hospital</i>	
centr _j	=1 if hospital <i>j</i> is central
dist _j	=1 if hospital <i>j</i> is district
epe _j	=1 if hospital <i>j</i> is EPE
univ _j	=1 if hospital <i>j</i> is university
espec _j	=1 if hospital <i>j</i> is specialized in cardiology
medic _j	no. of cardiologists in hospital <i>j</i>

On the side of hospital characteristics, we considered a set of binary variables to control whether the hospital is central, district and level-1 (**centr_j** e **dist_j**). This legal classification of NHS hospitals reflects the number of specialties that each hospital is prepared to deal with, being this number higher in central and smaller in level-1 hospitals. As such, this provides us with an indication of qualification of human resources and available technology at each hospital.

Also with a dummy variable (**univ_j**), we controlled if the hospital is a university hospital, since the scope of university hospitals has additional educational objectives compared to non-university hospitals, which may be reflected in the style of practice.

Another dummy variable (**epe_j**) takes the value 1 if the hospital, in that particular year, is a publicly held corporatized health care provider, being the reference class hospitals run under the traditional bureaucratic management of public services.¹¹ This variable aims at capturing any impacts of different incentives schemes and management cultures in hospitals' clinical profile. Finally, for obvious reasons, we controlled if the hospital where the patient is treated is specialized in cardiology (**espec_j**).

¹¹ In Portugal, the corporatization of NHS hospitals begun in December 2002 when 31 public hospitals were taken from under the direct administration of Government and transformed in profit-oriented corporations, with the aim of organizing the delivery of care subject to cost control and efficiency in the allocation of resources. In section 8 we present more detailed information on the corporatization of NHS hospitals in Portugal.

Additionally, we considered the number of physicians with differentiated training in cardiology in each hospital (physicians specialized in cardiology, paediatric cardiology and cardio-thoracic surgery). This variable (**medicj**) should be associated with greater ability to provide differentiated and intensive treatments in the area of heart disease.

In addition to the variables listed in table 1, we also introduced a set of binary variables controlling the year of each observation, in order to capture possible effects of the passage of time, or more precisely, effects felt over time that are transversal to the whole universe of NHS hospitals (for example, the spread of technology in the treatment of heart diseases).

4.3. Disease Staging

The choice of type of treatment for AMI is naturally conditional on the indication and/or counter indications of clinical nature for each particular patient. Such clinical specificity must be considered when comparing treatment choices, resource use and outcomes. Therefore, any evaluation of the appropriateness of care received should take into account the health status of the patient when first seen by the physician (Louis and Gonnella, 2005).

Accordingly, in order to control for the severity of illness of patients, we previously conducted a Disease Staging classification of each record on our data set. Disease Staging is a patient classification system, initially developed by Gonnella and Goran (1975) and Gonnella et al. (1976), that uses diagnostic findings to produce clusters of patients who require similar treatment and have similar expected outcomes. It can be implemented in a manual basis on detailed medical records, or in a computerized version which uses information on discharge records. The output of this classification system is a measurement of the severity of specific and well-defined medical diseases, where severity is defined as the risk of organ failure or death (Gonnella et al., 1984).

Disease Staging can be used to classify patients for a number of applications such as assessment of quality of care, diagnostic efficiency of physicians, analysis of outcomes or case-mix classification for analysis of resource utilization and reimbursement. It has

shown to be as good as some risk adjustment mechanisms that require data collected from medical records (Thomas and Ashcroft, 1991) and to predict resource use reasonably well (Coffey and Goldfarb, 1986). For purposes of measuring the clinical case-mix of a hospital, Disease Staging proved to be superior to Diagnosis Related Groups (DRG) based methods because it avoids the potential biases that are due to strategic behaviour by hospitals designed to maximize payments (Dor and Farley, 1996). According to Taroni et al. (1992), other than the DRGs, Disease Staging has been the most widely used patient classification system in the United States.

In Disease Staging, patients are classified into disease categories, based on the diagnoses and complications listed on the discharge abstract. These are relatively homogeneous with respect to the underlying medical condition or disease process. Each disease category, in turn, is subdivided into stages based on the clinical implications of complications and comorbidities. As referred by Taroni et al. (1992), these stages have clinical significance in choosing a therapeutic modality, as well as impacting on patient prognosis. There are four major stage levels to classify the manifestations of a disease (see table 2), and subdivisions of these stage levels. All stage levels are ordinal, with risk of death increasing with each higher stage level.

Table 2: Major stage levels of Disease Staging

Stage	Description
1	a disease with no complications
2	the disease as local complications
3	the disease involves multiple sites, or as systemic complications
4	death

In the computerized version, the Disease Staging classification of patients is done by assigning disease categories and stages to the ICD-9-CM diagnosis codes found on automated hospital discharge abstract data, a massive task which is done with a software package developed for that task.^{12 13}

¹² The MEDSTAT Group, Inc. (a subsidiary company of the Thomson Healthcare, Inc., which was latter renamed Thomson Medstat) developed Disease Staging criteria for high-incidence diseases and a computer software to apply the Disease Staging criteria to hospital discharge data. In this work the version 5.23.4 of the Medstat Disease Staging Software was used.

The data base where Portuguese NHS hospital discharge records are collected allows for the coding of up to twenty diagnostics in each record. The Disease Staging software assigns a disease category and a stage for every diagnosis, but there is only one principal disease category and the corresponding principal stage. In our statistical procedure we only used information on the principal disease category.

The complete list of stage levels is ordinal in nature of each medical problem, which means that a given stage may have different implications for resource use, treatment and prognosis for different diseases. Hence, stages of severity cannot always be compared across diseases. However, this feature does not cause complications in our empirical study because all records of our selected sample were assigned by the Disease Staging software one of two principal disease categories which have similar stage level subdivisions: coronary artery disease with prior coronary revascularization (coded as ‘cvs10’) and coronary artery disease without prior coronary revascularization (coded as ‘cvs11’).

Table 3 presents the full description of the clinical criteria used in cvs10 and cvs11 disease categories defined in the Disease Staging software.

¹³ The Disease Staging classification of our data was computed by Professor Carlos Costa and Professor Silvia Lopes, at the ENSP – National School of Public Health in Lisbon, who kindly acceded to our request.

Table 3: Clinical criteria for Disease Staging

Coronary artery disease with prior coronary revascularization (cvs10)	
Stage	Description
1.01	Coronary atherosclerosis or asymptomatic chronic ischemic heart disease or old myocardial infarction
1.02	Chronic stable exertional angina or chronic ischemic heart disease
2.01	Progressing angina pectoris or exertional myocardial ischemic at low workload or old myocardial infarction with low ejection fraction
2.02	Prinzmetal's variant angina
2.03	Angina with hypertrophy or akinesia or dyskinesia or S3 galop or S4 galop
2.04	Unstable angina pectoris
3.01	Acute inferior or posterior wall myocardial infarction
3.02	Acute inferior or posterior wall myocardial infarction with heart block or pericarditis
3.03	Acute inferior or posterior wall myocardial infarction with left ventricular thrombus
3.04	Acute inferior or posterior wall myocardial infarction with left ventricular aneurysm
3.05	Acute inferior or posterior wall myocardial infarction with CHF
3.06	Acute anterior wall myocardial infarction
3.07	Acute anterior wall or all other myocardial infarction with low ejection fraction
3.08	Acute anterior wall myocardial infarction with heart block or pericarditis
3.09	Acute anterior wall myocardial infarction with ventricular thrombus formation
3.10	Acute anterior wall myocardial infarction with ventricular aneurysm
3.11	Acute anterior wall myocardial infarction with CHF
3.12	Acute myocardial infarction with pulmonary embolism
3.13	Acute myocardial infarction with cerebrovascular accident
3.14	Acute anterior myocardial infarction with papillary muscle rupture or ventricular septal rupture
3.15	Coronary artery disease with ventricular fibrillation or shock
3.16	Coronary artery disease with cardiac arrest
4.00	Coronary artery disease with death
Coronary artery disease without prior coronary revascularization (cvs11)	
Stage	Description
1.01	Old myocardial infarction or coronary atherosclerosis or chronic ischemic heart disease
1.02	Chronic stable exertional angina
2.01	Progressing angina pectoris or exertional myocardial ischemic at low workload or old myocardial infarction with low ejection fraction
2.02	Prinzmetal's variant angina
2.03	Angina with hypertrophy or akinesia or dyskinesia or S3 galop or S4 galop
2.04	Unstable angina pectoris
3.01	Acute inferior or posterior wall myocardial infarction
3.02	Acute inferior or posterior wall myocardial infarction with heart block or pericarditis
3.03	Acute inferior or posterior wall myocardial infarction with left ventricular thrombus
3.04	Acute inferior or posterior wall myocardial infarction with left ventricular aneurysm
3.05	Acute inferior or posterior wall myocardial infarction with CHF
3.06	Acute anterior wall myocardial infarction
3.07	Acute myocardial infarction with low ejection fraction
3.08	Acute anterior wall myocardial infarction with heart block or pericarditis
3.09	Acute anterior wall myocardial infarction with ventricular thrombus formation
3.10	Acute anterior wall myocardial infarction with ventricular aneurysm
3.11	Acute anterior wall myocardial infarction with CHF
3.12	Acute myocardial infarction with pulmonary embolism
3.13	Acute myocardial infarction with cerebrovascular accident

- 3.14 Acute anterior myocardial infarction with papillary muscle rupture or ventricular septal rupture
 - 3.15 Coronary artery disease with ventricular fibrillation or shock
 - 3.16 Coronary artery disease with cardiac arrest
 - 4.00 Coronary artery disease with death
-

As we can see, both disease categories have 23 stage levels of severity, with similar descriptions. The main difference between `cvs10` and `cvs11` is that in the first case the patient had a coronary revascularization prior to the current admission episode. Such information might be important to understand the type of treatment prescribed by doctors because of possible implications in terms of clinical indication for coronary revascularizations in patients with prior revascularizations.

Concluding, we controlled for the severity of illness of patients by introducing in the logistic estimation two variables: the variable `cvs10i` which is a dummy variable that takes the value 1 if the patient was diagnosed as having had prior coronary revascularization and 0 if otherwise, and `stagei` which takes integers from 1 to 23 reflecting increasing severity of illness.

4.4. Data

The data analyzed came from the official registry of inpatient episodes and outpatient surgeries in Portuguese NHS hospitals, held by the Central Administration of the Health System (ACSS), in the period of 2000 to 2008. These records are coded according to the international classification of diseases ICD-9-CM and also classified through the Portuguese DRG system, which is based on the version 21.0 of the AP-DRG grouper.

We analyzed all AMI episodes which, according to the ICD-9-CM classification, we defined as corresponding to episodes with diagnosis coded with 410 and all its variations (410x and 410xx), amounting to a total of 41 different codes.

This universe of cases diagnosed with AMI was distributed according to the type of treatment received by patients, as defined in the previous section. Thus, patients identified as having received procedure “percutaneous transluminal angioplasty” (code 360 and its variations – a total of 10 procedures) and/or procedure “bypass” (code 361 and its variations – also a total of 10 procedures), were classified as having received

intensive treatment. The remaining episodes of AMI that were not referenced to another hospital were classified as having received non-intensive treatment.

We dropped from our data set all registries that occurred in specialized hospitals, except for those in cardiology specialized hospitals, which, as we already mentioned, were controlled with a dummy variable. We also considered only records that were coded with admission type ‘emergency’, dropping episodes that had programmed surgery or that were transferred from other hospitals. Finally, we excluded episodes that ended with the patient being transferred to another hospital or being sent home to receive domiciliary care, and episodes where the patient left the hospital against medical indication, leaving us only ‘complete’ episodes that ended either with the clinical discharge of the patient or death.¹⁴

The final sample was composed of 89,026 episodes of inpatient care in NHS hospitals with diagnosis of AMI, as defined above. Of these, 64% were male patients. The average age of patients was 68 years, being the standard deviation 13.4 years. The age distribution of patients in the sample is illustrated in Figure 1, in which we distinguish male and female patients. The age distribution of male and female patients is very similar, but centred in the first case on a lower average age. Average age is 65 in male patients and 74 in female patients, with similar standard deviations (13 for males and 12 for females). With data showing a similar sex-age profile, Williams et al. (2004) found that the impact of the patient’s sex disappeared when the intensity of treatment was controlled for the age of the patient, suggesting that the differences between sexes were in fact merely a reflection of the effect of age, which was on average highest in female patients.

¹⁴ Similar exclusionary criteria are used by Costa and Lopes (2007) in an assessment of the performance of Portuguese NHS hospitals.

Figure 1: Age and sex of patients with AMI admitted from 2000 to 2008

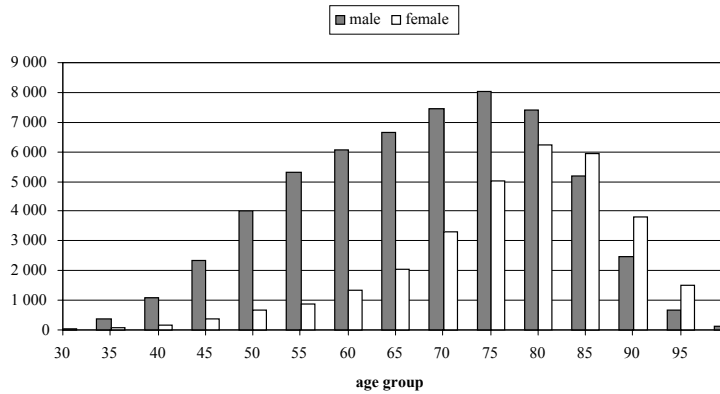


Table 4 presents, for each year, the proportion of patients with AMI and age ≤ 55 years treated intensively and the proportion of patients with AMI and aged 65 years treated intensively, which in practice corresponds, respectively, to the unconditional probability of a patient with 55 or less years receiving intensive care and a patient with 65 or more years receiving intensive care. Also in table 4 we present the difference between these two proportions, and in table 5 we present similar information but disaggregated by sex.

As can be seen in both tables, the frequency of cases of AMI treated intensively has been increasing steadily over the years. This type of treatment is more frequent in patients with 55 or less years compared to patients aged 65 or more years, a differential that grew since 2000 until 2006, when we observe an inflexion in the growth trend. Concerning the sex of patients, male patients are those who have received intensive treatment of AMI more frequently, and the differential between men and women as also been growing over time.

Table 4: Differences in treatment of AMI according to age of patients

Year	% AMI treated intensively in patients aged ≤ 55	% AMI treated intensively in patients aged ≥ 65	Differential p.p.
2000	0.285	0.107	0.178
2001	0.327	0.128	0.199
2002	0.391	0.157	0.234
2003	0.455	0.178	0.276
2004	0.544	0.218	0.326
2005	0.579	0.242	0.337
2006	0.616	0.274	0.342
2007	0.610	0.281	0.329
2008	0.613	0.293	0.320

Table 5: Differences in treatment of AMI according to sex of patients

Year	% AMI treated intensively in male patients	% AMI treated intensively in female patients	Differential p-p.
2000	0.186	0.110	0.076
2001	0.227	0.137	0.089
2002	0.265	0.158	0.107
2003	0.319	0.178	0.141
2004	0.375	0.204	0.171
2005	0.410	0.229	0.180
2006	0.446	0.257	0.189
2007	0.457	0.259	0.198
2008	0.470	0.276	0.195

Table 6 presents a statistical summary of the relevant variables, based on data from all years, distinguishing the group of patients who have received intensive treatment from those who have received non-intensive treatment. Patients who have received intensive treatment are on average more frequently male (76% are males) and younger (62 years in average), compared to patients who received non-intensive treatment (59% are males and 71 years old on average). In table 6 we also present the p-values of univariate analyses to assess the statistical significance of differences in the explanatory variables between the two groups of patients. Differences in the means of continuous variables were evaluated with t-tests and differences in proportions of categorical variables were evaluated with chi-squared tests. As we can see, all variables but **cvs10i** have statistically significant different means between the two groups of patients.

Table 6: Summary statistics of explanatory variables

Variable	All patients			Non-intensive treatment			Intensive treatment			P-value
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
sexi	89,026	0.356	0.479	62,008	0.405	0.491	27,018	0.242	0.429	<0.001
agei	89,026	68.426	13.408	62,008	71.080	12.956	27,018	62.335	12.405	<0.001
fini	89,026	0.790	0.407	62,008	0.796	0.403	27,018	0.777	0.416	<0.001
stagei	89,026	3.895	4.230	62,008	4.001	4.331	27,018	3.651	3.980	<0.001
cvs10i	89,026	0.022	0.147	62,008	0.023	0.148	27,018	0.021	0.142	0.077
centrj	89,026	0.396	0.489	62,008	0.332	0.471	27,018	0.541	0.498	<0.001
distj	89,026	0.587	0.492	62,008	0.645	0.479	27,018	0.454	0.498	<0.001
univj	89,026	0.180	0.385	62,008	0.149	0.356	27,018	0.252	0.434	<0.001
epej	89,026	0.412	0.492	62,008	0.385	0.487	27,018	0.474	0.499	<0.001
especj	89,026	0.037	0.189	62,008	0.017	0.129	27,018	0.084	0.277	<0.001
medicj	89,026	14.864	14.513	62,008	12.752	13.234	27,018	19.711	16.074	<0.001

5. Results

In table 7 we present the results of the logistic regression model estimated by maximum likelihood. In addition to the directly estimated coefficients, whose interpretation is of little interest, we also computed odds-ratios for the probability of receiving intensive treatment against the probability of receiving non-intensive treatment.¹⁵ The same table displays the average marginal effect (AME) and the marginal effect at the mean value (MEM) of each explanatory variable in the probability of receiving intensive treatment.

To assess the global significance of the model we performed a Pearson's generalized chi-squared test and to evaluate the goodness-of-fit we computed a pseudo R^2 measure.¹⁶

Without considering the Rogers (1993) correction of standard deviations for intra-cluster correlation, all variables (except for **epej**) present estimated coefficients with statistical significance at the level of 1%. The correction reduces the significance of variables, with some turning out to be relevant only with at a significance level of 5% or 10%, or even completely losing the statistical significance (the case of **epej** and **univj**).

The estimated odds-ratios tell us that the probability of receiving intensive care of AMI decreases 4.8% for each additional year of age. It can also be seen that this probability in women is 34% lower than in men. These effects are highly significant, even after the

¹⁵ Odds-ratios can be used to infer the direction and significance levels of the effects of explanatory variables. An odds-ratio > 1 for variable **sexi** (which takes the value 1 when the patient is female) would indicate that being female increased the probability of obtaining intensive treatment compared to males.

¹⁶ The model estimates from a logistic regression are maximum likelihood estimates obtained through an iterative process, so they do not necessarily minimize variance. Thus, the Ordinary Least Squares (OLS) approach to goodness-of-fit does not apply. To evaluate the goodness-of-fit of logistic models there are several pseudo R^2 with slightly different interpretations from an OLS R^2 . Here we report McFadden's

(1974) widely used pseudo R^2 , which is given by $R^2 = 1 - \frac{\ln \hat{L}_{full}}{\ln \hat{L}_0}$, where $\hat{L}_{full}$ is the estimated likelihood

for the model with all predictors (full model) and $\hat{L}_0$ is the estimated likelihood for the model without predictors (intercept model). The analogy to an OLS R^2 is that the log likelihood of the intercept model is treated as total variability in the dependent variable, and the log likelihood of the full model is treated as the sum of squared errors. Thus, the ratio of the two likelihoods suggests the level of improvement over the intercept model offered by the full model. The smaller this ratio, the greater the improvement and the higher the R^2 .

correction of Rogers. The interpretation of marginal effects allows us to have another perspective on the impact of variables. On average, an additional year of age implies a decrease of 0.8 percentage points on the probability of the patient with AMI receiving intensive care. For a patient with age similar to the average of the sample analyzed, this decrease is 1.0 percentage point. On the other hand, a female patient has, on average, a probability of receiving intensive care 7.2 percentage points lower than a male patient.

As we already mentioned, the age structure of patients in the sample is slightly distinct for male and female patients, with the latest having higher age on average. This raises the question of correlation between sex and age of patients admitted to hospitals with AMI, studied by Williams et al. (2004), who suggest that the differences in treatment observed between sexes might actually reflect differences in treatment based on age of patients.

Technically, in a logistic regression model, when two explanatory variables are highly correlated, the consequences are similar to what happens in a linear regression model: multicollinearity does not bias estimates of coefficients but makes them more unstable. The standard deviations tend to be very high, and it is difficult to distinguish the impact of each explanatory variable on the dependent variable (Allison, 1999).

In our data, sex and age of patients present a correlation coefficient of 0.32. It is difficult to classify this degree of correlation as high or low, and realize if this results in problems for the estimation of the model. Multicollinearity is more a matter of degree, and there is not an irrefutable test for its detection. Nevertheless, there is a set of diagnostic procedures that give us an indication of when the multicollinearity becomes a problem.

Firstly, there is evidence of multicollinearity problems when most of the independent variables in the regression model have no statistical significance when taken individually, but globally the estimated model has statistical significance. However, as can be seen from table 7, this is not the case for the model that we have estimated, with most variables presenting high statistical significance.

Another clue of multicollinearity problems is high sensitivity of estimated coefficients to small changes in model specification. Accordingly, we estimated the model with the other two classical functional forms for binary choice models, probit and linear probability model, and found that the marginal effects of variables age and sex do not suffer relevant changes (see results in appendix 2).

The third test performed consists in calculating the variance inflation factor (VIF)¹⁷, which gives an indication of how much the variance of an estimated coefficient is increased due to collinearity. We have found VIF values well below 2.5 for almost all variables, with the exception of variables **centrj** and **distj**, with VIF near 10, which is not surprising since these are two dummy variables for a same classification with three classes.

Finally, we estimated a logit model with an interaction term between variables **sexi** and **agei** in order to capture potential crossed effects of sex and age on the dependent variable. The estimated coefficient of the interaction term is statistically significant but the complete interaction effect is not significant for many observations, and on average it is not statistically significant (the mean z-statistic of the interaction effect is 0.34).¹⁸ Also the inclusion of the interaction term didn't result in a relevant improvement of the global fit of the model (the pseudo R^2 suffered an increase of less than 0.001). More important, the estimated coefficients of all other explanatory variables, including sex and age, retain their sign, and their magnitude and statistical power suffers only minor changes. The complete results and the estimated interaction effects are presented in appendix 3.

In conclusion, according to the tests performed there is no evidence of multicollinearity problems in the estimation of the effects of sex and age on the probability of a patient with AMI receiving intensive treatment. Thus, unlike Williams et al. (2004), our sample

¹⁷ For each independent variable, this indicator is simply equal to the inverse of tolerance for this variable, which in turn equals $(1-R^2)$ of a linear regression of that variable on all other independent variables. These indicators do not have an absolute cut-off to classify the degree of multicollinearity, being used as rule-of-thumb for indication of multicollinearity problems tolerance levels less than 0.4, 0.2 or 0.1 which, conversely, means VIF values exceeding 2.5, 5 or 10.

¹⁸ As we will see in detail in section 7, the complete interaction effect is not equal to the marginal effect of the interaction term, and its statistical significance cannot be determined from the z-statistic reported in the regression output.

does not reveal confusion between the effects of age and sex enough to ignore the individual effects of each variable.

Although sex and age are the variables whose results are the main focus of this study, the analysis of estimated odds-ratios for the remaining variables is also interesting. Notice that our results also suggest that having NHS financial coverage is associated with a lower probability of receiving intensive care, but this effect loses statistical significance with the correction of standard deviations for intra-cluster correlation. Concerning the Disease Staging variables, we can see that the probability of receiving intensive care is lower in patients with prior revascularizations and also that it decreases as the severity of illness increases, both effects being statistically significant at a 5% level, at least. Over the years the probability of receiving intensive care of AMI is increasing, reflecting a technological evolution in the treatment of AMI based on the increment of intensivity. The probability is higher in central hospitals, lower in district hospitals and the lowest in level-1 hospitals, an expected result that reflects the degree of technological endowment and differentiation in hospitals. The probability of the treatment being intensive is also higher in hospitals specialized in cardiology and lower in university hospitals, although the second of these two effects loses statistical significance with the correction of standard deviations. The same happens with the variable that distinguishes EPE hospitals from traditional public hospitals. Finally, as expected, being in a hospital where specialist physicians are more available is associated with a greater probability of receiving intensive treatments.

Table 7: Estimation results of the logistic regression model for the probability of patients with AMI receiving intensive treatment

Variable	Coefs.	Z-stat	Z-stat Rogers	Odds-Ratios	AME	MEM
sexi	-0.424	(22.77)***	(11.36)***	0.655	-0.072	-0.083
agei	-0.049	(75.01)***	(29.96)***	0.952	-0.008	-0.010
fini	-0.221	(10.97)***	(2.08)**	0.801	-0.038	-0.043
stagei	-0.013	(6.52)***	(2.16)**	0.987	-0.002	-0.002
cvs10i	-0.463	(8.52)***	(7.57)***	0.629	-0.079	-0.090
centrj	1.412	(14.55)***	(2.53)**	4.106	0.242	0.275
distj	0.881	(9.21)***	(1.77)*	2.414	0.151	0.172
epej	-0.039	(1.95)*	(0.19)	0.961	-0.007	-0.008
univj	-0.220	(5.65)***	(0.70)	0.802	-0.038	-0.043
especj	0.859	(15.29)***	(2.49)**	2.361	0.147	0.167
medicj	0.021	(19.30)***	(2.00)**	1.022	0.004	0.004
y2001	0.309	(7.04)***	(4.01)***	1.363	0.053	0.060
y2002	0.561	(13.28)***	(6.24)***	1.753	0.096	0.109
y2003	0.818	(19.55)***	(5.54)***	2.267	0.140	0.159
y2004	1.082	(26.10)***	(5.05)***	2.952	0.185	0.211
y2005	1.252	(30.14)***	(5.29)***	3.498	0.214	0.244
y2006	1.510	(35.88)***	(6.13)***	4.527	0.258	0.294
y2007	1.587	(37.24)***	(5.94)***	4.890	0.272	0.309
y2008	1.696	(39.96)***	(6.00)***	5.450	0.290	0.330
Constant	0.313	(2.88)***	(0.60)	-	-	-

Observations: 89,026
 Absolute value of z statistics in parentheses
 * significant at 10%; ** significant at 5%; *** significant at 1%
 Pseudo $R^2 = 0.1596$
 Prob>chi² = 0.0000

6. Welfare implications of disparities of treatment based on gender

There is a substantive body of literature documenting disparities based on social group of patients, of which we refer only a small fraction. The exploration of the causes of discrimination and the resulting disparities is less frequent, particularly in terms of empirical analysis of the magnitude and importance of these causes.

Even scarcer is the analysis of the welfare implications of health care disparities. Trying to bridge that gap, in this section we quantify some of the consequences of the

disparities found between the treatment given to men and women, adopting a methodology similar to receiver operating characteristics analysis.¹⁹

We begin with the assumption that men are not discriminated against and women are, in a way that the standard of treatment of AMI in women is biased in favour of less intensive treatment, where as for men the standard of treatment is unbiased. As a corollary, the standard of treatment in men is considered the correct (unbiased) choice rule according to the relevant characteristics of the patient (diagnostic, severity, cardiac disease history and age) and of hospital.

We will use the estimated standard of treatment in men to predict if a given woman should or shouldn't have received intensive treatment according to that standard, and compare the predicted choice with the real choice (i.e., compare real treatment choice with predicted choice).

Accordingly, the first step of the analysis was to estimate a logit model similar to that presented in the previous section but excluding the variable **sex** and restricting the sample to male patients. The resulting model has similar results to the global model, with coefficients of explanatory variables presenting the same signs and statistical significance (see table 8). These estimates constitute the standard of treatment in male patients, which we hypothesized as being the unbiased choice rule.

¹⁹ We do not present here a complete welfare analysis since we do not have all the needed information, namely about costs of treatments.

Table 8: Estimation results of the logistic regression model for the probability of patients with AMI receiving intensive treatment (subsample sexi=0)

Variable	Coefs.	Z-stat
agei	-0.047	(61.57)***
fini	-0.202	(8.60)***
stagei	-0.015	(6.14)***
cvsl0i	-0.513	(8.38) ***
centrj	1.348	(11.72) ***
distj	0.824	(7.27) ***
epej	-0.037	(1.54)
univj	-0.275	(5.90) ***
especj	0.703	(10.23) ***
medicj	0.025	(19.01) ***
y2001	0.308	(6.09) ***
y2002	0.572	(11.76) ***
y2003	0.855	(17.68) ***
y2004	1.157	(24.05) ***
y2005	1.339	(27.71) ***
y2006	1.589	(32.44) ***
y2007	1.664	(33.49) ***
y2008	1.778	(35.96) ***
Constant	0.139	(1.09)

Observations: 57,340
Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
Pseudo R² = 0.1473
Prob>chi² = 0.0000

Next we ran the subsample of female patients through the estimated model and got the predicted probabilities, for every female patient, of having intensive treatment $\hat{\Pr}[Y_{ij} = 1]$. Intensive treatments were then predicted according to the rule $\hat{Y}_{ij} = 1$ when $F(\mathbf{X}'_i\boldsymbol{\beta}, \mathbf{Z}'_j\boldsymbol{\delta}) > 0.5$.

As a result, we have information on actual intensive treatment choice for men and women and predicted intensive treatment choice according to the unbiased standard of treatment in men. The comparison between the two allows us to analyse the welfare implications of the bias present in actual choice of treatment in women.

The following analysis was done in the fashion of receiver operating characteristics (ROC) analysis, a methodology that was first developed in signal detection theory

(Lusted, 1971; Egan, 1975) and latter was adopted in areas such as psychology (Swets, 1996) and medical decision making (Lloyd, 1998; Zhou, 2002).

For both men and women subsamples we constructed confusion matrixes (also called contingency tables) with the structure defined in table 9.

Table 9: Confusion matrix for actual treatment choices and predicted choices under same treatment standard as men

		Actual treatment choice	
		Intensive	Non-intensive
Predicted treatment choice	Intensive	A	B
	Non-Intensive	C	D

The four possible outcomes expressed in the matrix are interpreted as follows: A corresponds to the number of patients that should be treated intensively (according to the unbiased standard of treatment) and that actually received intensive treatment – we call these cases Correctly Treated; B corresponds to the number of patients that should be treated intensively but didn't receive such treatment – these cases are Undertreated; C is the number of patients that shouldn't be treated intensively but received intensive treatment – we call these Overtreated; and finally D is the number of patients that shouldn't be treated intensively and actually didn't received intensive treatment – Correctly Not Treated.²⁰

The rates (or metrics) of interest that can be drawn from the matrix are the Rate of Undertreatment, given by $RU=B/(A+B)$, which corresponds to the proportion of patients that didn't receive intensive treatment in the total of patients that should have received intensive treatment; the Rate of Overtreatment given by $RO=C/(C+D)$, reflecting the proportion of patients that received intensive treatment in the total of patients that shouldn't have received intensive treatment; and the Accuracy Rate given

²⁰ The reader might notice the abusive classification of D cases as Correctly Not Treated, since they actually received treatment, but not intensive.

by $AR=(A+D)/(A+B+C+D)$, which reflects the proportion of patients that were correctly treated according to the standard in the total of patients.²¹

Tables 10 and 11 present the confusion matrixes for, respectively, male and female patients, where the predicted choices of treatment are drawn from the model estimated solely with male patients (as already been said, the model that sets the unbiased rule of treatment). On the same tables we also present the respective metrics of interest.

Table 10: Confusion matrix for actual treatment choices for men and predicted choices under same treatment standard as men

		Actual treatment choice	
		Intensive	Non-intensive
Predicted treatment choice	Intensive	8,826	5,289
	Non-Intensive	11,642	31,583
RU = 37.47%			
RO = 26.93%			
AR = 70.47%			

Table 11: Confusion matrix for actual treatment choices for women and predicted choices under same treatment standard as men

		Actual treatment choice	
		Intensive	Non-intensive
Predicted treatment choice	Intensive	1,964	2,148
	Non-Intensive	4,586	22,988
RU = 52.24%			
RO = 16.63%			
AR = 78.75%			

Taking the standard of treatment in men as the unbiased rule of choice we found a rate of undertreatment in women of about 52%, i.e., 52% of the women that should have received intensive treatment didn't received it, a rate that compares to the 37% found in men. On the other hand, women also seem to be less overtreated since only 17% of

²¹ In the original form of a ROC analysis, where the objective is to evaluate the predictive power of a system (e.g., capacity of doctors to diagnose correctly), A would be called the number of true positives, B false positives, C false negatives and D true negatives. For the purpose of evaluating predictive power, the usual metrics that are drawn from the matrix are the true positives rate ($TPR=A/(A+C)$, also called sensitivity), the false positives rate ($FPR=B/(B+D)$, equal to 1-specificity) and the accuracy ($ACC=(A+D)/(A+B+C+D)$).

women that shouldn't have received intensive treatment ended up receiving such treatment, comparing to 27% of overtreatment in men. These results favour the previous finding that women are globally treated less intensively, highlighting the disparities in the standard of treatment of men and women.

From the results show in the tables we can also conclude that treatment decisions are actually more accurate, on average, in women than in men, since the higher rate of undertreatment in women is globally offset by the lower rate of overtreatment. Nevertheless, the differential in the rate of undertreatment in men and women is relevant, and reflects women being considerably more undertreated than man according to the standards of treatment applied to the latter.

With the available data we cannot fully assess the consequences of such undertreatment in women. Nevertheless, we present here some interesting statistics on the probability of death of the patients of our sample which might help to shed some light on the issue of consequences of differences on treatment standards in men and women.

Recall that our sample was constructed in order to include only 'complete' episodes that ended either with clinical discharge or death. In the following table we present conditional probabilities for an episode ending with the death of the patient, based on simple counts from our sample, and the P-value of the chi-squared significance test for the differences (we used this test since all considered variables are dichotomous).

Table 12: Conditional probabilities of death

Probability	P-value for χ^2 test	
$Pr(\text{death} \mid \text{woman})$	19%	<0.001
$Pr(\text{death} \mid \text{man})$	11%	
$Pr(\text{death} \mid \text{non-intensive treatment})$	18%	<0.001
$Pr(\text{death} \mid \text{intensive treatment})$	4%	
$Pr(\text{death} \mid \text{woman, undertreated})$	23%	<0.001
$Pr(\text{death} \mid \text{woman, correctly not treated})$	11%	
$Pr(\text{death} \mid \text{woman, correctly treated})$	6%	0.047
$Pr(\text{death} \mid \text{woman, overtreated})$	7%	

Notice that, in line with most evidence found in the literature, women with AMI die more frequently than men (1.7 times more, to be precise, $P < 0.001$), and also that patients that didn't receive intensive treatment had a probability of death 4.5 times

higher ($P < 0.001$). Restricting to the subsample of women who didn't receive intensive treatment, we observe that the probability of death was 23% for undertreated female patients, which is considerably higher than the 11% for female patients correctly not treated ($P < 0.001$). Hence, undertreatment in women with AMI is apparently associated with a higher probability of death. When looking at female patients that did receive intensive treatment, we find a slightly higher probability of death in overtreated patients compared to correctly treated ones, although this difference is statistically significant only at a 95% confidence level.

7. Testing for statistical discrimination

Based in a Balsa and McGuire (2003) model of doctor choice of treatment, we presented earlier two potential sources of health care disparities based on demographic group: taste-based discrimination and statistical discrimination. We also mentioned that we are aware of few studies trying to measure the magnitude and the importance of these different sources of disparities.

In this section we present an empirical test of statistical discrimination as the underlying mechanism for the discrimination of women in terms of treatment for AMI in Portuguese NHS hospitals, which we documented in this essay.

Taste-based discrimination refers to disparities in treatment that are caused by prejudice or bias felt by doctors against members of particular social groups. As it is defined, this type of discrimination must operate at the individual (doctor) level, and not at an aggregate (hospital) level.²²

Our data set includes information from the patient and the hospital where it received treatment, but not information about the doctor who treated the patient. Therefore, we cannot test the existence of taste-based discrimination. However, we can explore the

²² Taste-based discrimination operating at the hospital level would mean that disparities are observed if all doctors in a certain hospital have a taste to discriminate and all doctors in another hospital do not discriminate.

information about hospital characteristics to test for statistical discrimination, as statistical discrimination can operate at the aggregate level.

Mechanisms of statistical discrimination, such as ‘rational profiling’, arise when doctors, facing uncertainty about the patient’s conditions, rely on prior statistical information about the prevalence of illness associated with different social groups, to improve their inference about diagnoses and treatment choices. Such behaviour can have roots in personal aspects of doctors (e.g., academic course or professional experience), but can also easily be influenced by external factors related to the hospital where he/she works. For instance, in hospitals where financial pressure to reduce costs is increased, doctors may be led to perform less diagnostic tests and recur more often to prior information in order to make treatment choices, as a way to reduce resource usage or patient length of stay. Or if hospitals have to comply with certain performance and quality standards, doctors may be led to compensate uncertainty when treating patients by recurring to statistical discrimination mechanisms more frequently. Hence, statistical discrimination behaviour by doctors may be induced by hospital characteristics, and therefore, can be tested at the hospital level.

Returning to the theoretical model presented in section 2, in face of uncertainty doctors will select a threshold S^* for the observed severity level above which patients get intensive treatment, in order to maximize the expected benefit $(1 - \beta)\mu_i + \beta S$, where

$\beta = \frac{\sigma^2}{\sigma^2 + \sigma_\varepsilon^2}$ and $i \in \{M, W\}$. The reduction of diagnostic procedures would result in a

higher degree of uncertainty present when the doctor observes the signal of severity S , which is reflected in a higher variance (σ_ε^2) of the noise of the signal $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. As we said before, when the signal is noisier, β is lower and the doctor will put less weight on the signal and more on the mean severity.

In our data set, we have a relevant piece of information that captures financial and performance incentives on hospitals of the Portuguese NHS, the EPE variable, which identifies hospitals subject to corporatization. Corporatized hospitals were taken from under the direct administration of Government and transformed in profit-oriented corporations, with the aim of organizing the delivery of care subject to cost control and

efficiency in the allocation of resources. These hospitals (first designated SA and later EPE)²³ remain public property (100% owned by the state), but differ fundamentally from non-corporatized hospitals in terms of management instruments at its disposal. These hospitals acquire administrative and financial autonomy, have professionalized and independent boards of directors, accountable to the Ministry of Health through predetermined operational and financial contracted objectives, and have freedom to hire human resources under private labour contracts.

The administrative and financial separation from its main funder (the State, through the NHS) is put in practice with funding being attributed through contracts between the Ministry of Health and each hospital. In such contracts, the NHS and the hospital agree on quantities and types of services, based on the actual production of each hospital per line of production and estimated needs for the population, and agree on the prospective payment for the overall contracted production. These contracts also set financial and quality performance indicators that hospitals are bound to achieve. This logic is opposite to the traditional model of global budget with total reimbursement of costs, and constitutes an important feature – although not the only one – of the public hospital sector reform. All these changes aimed at creating incentives and provide NHS hospitals with the means to have a more efficient management.

In this context, the EPE status is interpreted as a characteristic that imposes increased financial pressure and performance targets on hospitals, providing an interesting hospital differencing factor that allows us to test for statistical discrimination.

Another relevant feature of the theoretical model is that as a result of the statistical discrimination mechanism doctors find it optimal to set a higher threshold for the group with a lower mean severity, that is, $\mu_W < \mu_M \Rightarrow S_W^* > S_M^*$. Accordingly, statistical discrimination might explain the observed differences in AMI treatment between male and female patients only if doctors observe average severity levels and females have a lower average severity level. This is, in fact, the case in our sample: the variable **stagei**, which consists of the severity stage that resulted from the Disease Staging classification,

²³ “SA – Sociedade Anónima” is the Portuguese designation for a limited liability company, in the United Kingdom, or a joint-stock corporation, in the United States. “EPE – Entidade Pública Empresarial” is a state-owned enterprise.

has a mean value of 4.1 for male patients (standard deviation is 4.3.) and 3.8 for female patients (standard deviation is 4.3).²⁴

Given these two characteristics of the setting being studied, we find it relevant to test if discrimination of women in treatment of AMI is sensitive to hospitals being EPE and non-EPE. If it is, this means that EPE incentives at hospital level may be influencing doctors' choices of treatment relative to patients' social groups. This can work, as we explained, through a statistical discrimination mechanism.

We performed such test with the estimation of an interaction effect between the relevant variables, sex of patient and EPE status. In applied research, interaction terms are often estimated to infer how the effect of one independent variable on the dependent variable depends of the magnitude of another independent variable. In simple terms, we try to answer if the effect of patient sex on the type of treatment for AMI he/she receives is the same in both EPE and non-EPE hospitals.

To answer this question, we can run a regression to predict type of treatment as a function of a dummy variable for sex, a dummy variable for EPE status, the interaction between the two, and other covariates. In the case of linear models, if the coefficient on the interaction term is statistically significant, there is a difference between EPE and non-EPE hospitals in how sex affects treatment choice. However, such interpretation of interaction terms does not extend to non-linear models, such as logit and probit models.

As Ai and Norton (2003) noted, unlike in linear models, in non-linear models the complete interaction effect is not equal to the marginal effect of the interaction term, and its statistical significance cannot be determined from the z-statistic reported in the regression output.²⁵ We must compute the cross derivative of the expected value of the dependent variable, or in the case where interacted variables are dichotomous, the cross difference.

²⁴ Remember that **stagei** takes integer values from 1 to 23.

²⁵ It is common for researchers to misinterpret interaction terms in non-linear models. Ai and Norton (2003) found that 72 articles published on 13 journals listed on JSTOR, between 1980 and 2000, used interaction terms in non-linear models and with the exception of one, none interpreted the coefficient on the interaction term correctly.

One important implication of this is that the test for the statistical significance of the interaction effect must be based on the estimated entire cross derivative (or difference), not just on the coefficient of the interaction term. Also important is that the interaction effect is conditional on the independent variables, and it may have different signs for different values of covariates. Therefore, the sign of the coefficient of the interaction term does not necessarily indicate the sign of the interaction effect.

In their paper, Ai and Norton present cross-partial derivatives (or differences) for interaction effects in logit and probit models. In an analogous way, let our binary dependent variable Y depend on two independent variables x_1 and x_2 , their interaction and a vector of additional independent variables $\tilde{\mathbf{X}}$.²⁶ The expected value of the dependent variable, conditional on the independent variables, is

$$E[Y | x_1, x_2, \tilde{\mathbf{X}}] = \Pr[Y = 1 | x_1, x_2, \tilde{\mathbf{X}}] = F(\beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}) = F(\mathbf{X}\boldsymbol{\beta})$$

Since the interacted variables x_1 and x_2 are both dummy variables, the interaction effect is the discrete double difference (or cross difference) with respect to x_1 and x_2 :

$$\begin{aligned} \frac{\Delta^2 F(\cdot)}{\Delta x_1 \Delta x_2} &= \frac{\Delta \{F(\beta_1 + \beta_2 x_2 + \beta_{12} x_2 + \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}) - F(\beta_2 x_2 + \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}})\}}{\Delta x_2} = \\ &= F(\beta_1 + \beta_2 + \beta_{12} + \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}) - F(\beta_1 + \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}) - F(\beta_2 + \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}) + F(\tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}) \end{aligned}$$

Note that this complete interaction effect does not equal the marginal effect of just the interaction term $x_1 x_2$, which is

$$\frac{\Delta F(\cdot)}{\Delta(x_1 x_2)} = F(\beta_1 x_1 + \beta_2 x_2 + \beta_{12} + \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}) - F(\beta_1 x_1 + \beta_2 x_2 + \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}})$$

The asymptotic variance of the estimated interaction effect of two dummy variables in non-linear models is estimated consistently by

$$\frac{\partial}{\partial \boldsymbol{\beta}'} \left\{ \frac{\Delta^2 F(\cdot)}{\Delta x_1 \Delta x_2} \right\} \hat{\boldsymbol{\Omega}}_{\boldsymbol{\beta}} \frac{\partial}{\partial \boldsymbol{\beta}} \left\{ \frac{\Delta^2 F(\cdot)}{\Delta x_1 \Delta x_2} \right\}$$

²⁶ For simplicity of the exposition, we consider both patient and hospital variables in the same vector of covariates and dropped individual and hospital subscripts.

where $\hat{\Omega}_\beta$ is a consistent covariance estimator of $\hat{\beta}$.

Ai and Norton developed a STATATM program that computes the correct interaction effect, standard errors and z-statistics for each observation, for logit and probit models. We ran our logit model, presented in sections 4 and 5, and computed with that program the interaction between variables **sexi** and **epej**.

Table 13 presents the results of the logistic regression model estimated by maximum likelihood, with the standard errors adjusted for clustering on hospital, and table 14 presents the mean values of the interaction effects computed for every observation, mean standard errors and mean z-statistics.²⁷

²⁷ We do not present odds-ratios here because with interaction effects they cannot be interpreted in the same way as without interaction. The exponentiation of logistic coefficients, in this case, corresponds to the ratio of odds-ratios, which has no useful interpretation. See Ai and Norton (2003) for a complete demonstration of this.

Table 13: Estimation results of the logistic regression model for the probability of patients with AMI receiving intensive treatment, with interaction term between sex and EPE status

Variable	Coefs.	Z-stat Rogers
sexi	-0.382	(8.32)***
sexi*epej	-0.091	(2.53)**
agei	-0.049	(30.01)***
fñi	-0.222	(2.09)**
stagei	-0.013	(2.16)**
cvsl0i	-0.463	(7.59)***
centrj	1.412	(2.53)**
distj	0.880	(1.77)*
epej	-0.011	(0.05)
univj	-0.221	(0.71)
especj	0.860	(2.50)**
medicj	0.021	(2.00)**
y2001	0.308	(4.01)***
y2002	0.560	(6.24)***
y2003	0.815	(5.50)***
y2004	1.078	(5.02)***
y2005	1.247	(5.26)***
y2006	1.507	(6.11)***
y2007	1.584	(5.92)***
y2008	1.693	(5.98)***
Constant	0.307	(0.59)

Observations: 89,026
 Absolute value of z statistics in parentheses
 * significant at 10%; ** significant at 5%; *** significant at 1%
 Pseudo R² = 0.1596
 Prob>chi² = 0.0000

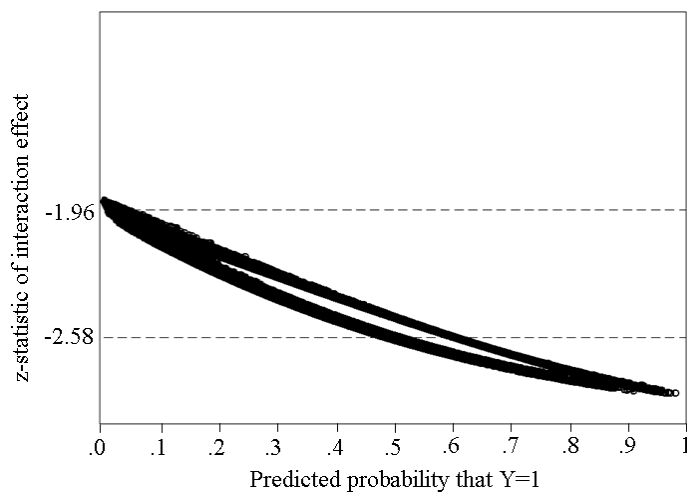
Table 14: Statistics of interaction effects between sex and EPE status

	Mean	Std. Dev.	Min	Max
Interaction effect	-0.0140	0.0061	-0.0229	-0.0005
Standard error	0.0059	0.0022	0.0002	0.0089
z-statistic	-2.2988	0.1985	-2.8503	-1.9159

As before, the estimation results for variables **sexi** and **epej** alone imply that women are less likely to receive intensive treatment for AMI than men, and that hospital status doesn't influence the probability of a patient receiving intensive treatment. However, the interaction term between the two variables is negative and statistically significant, suggesting that the negative effect of **sexi** in the probability of receiving intensive treatment is larger in EPE hospitals than in non-EPE hospitals.

We emphasize, though, that the coefficient of the interaction term is not the correct interaction effect. After computing the cross differences, we learn that the mean interaction effect is in fact negative, and negative in all observations, but varies largely among observations, as it does its statistical significance. In figure 2 we plot all z-statistics of the interaction effects against predicted probabilities. The interaction effect is statistically significant at the level of 5% (corresponding to z-statistics below the -1.96 line) for most observations, but is statistically significant at the level of 1% (corresponding to z-statistics below the -2.58 line) only for observations with predicted probability of receiving intensive treatment of around 0.6 and higher.

Figure 2: Z-statistics of interaction effects after logit estimation



In face of such results we conclude that the effect of patient sex on the type of treatment for AMI he/she receives is larger in EPE hospitals than it is in non-EPE hospitals, though evidence is stronger for patients with higher probability of receiving intensive treatment. We argue that this is compatible with statistical discrimination since the magnitude of sex based discrimination in AMI treatment depends on financial and performance incentives that hospitals are subject to. However this is not a complete analysis of the underlying causes of discrimination of women in terms of AMI treatment in the sense that we did not test the existence and the magnitude of other sources of discrimination, such as taste-based discrimination.

8. Conclusions

Our empirical study aimed at identifying the impact of age and sex of patients who suffered an AMI on the type of treatment received in Portuguese NHS hospitals from 2000 to 2008. Unlike other studies, the simultaneous consideration in the statistical procedure of age and sex of patients allows us to control for any effects of correlation between age and gender but does not entail loss of relevance of none of these variables in the explanation of the type of treatment received. Thus, our results suggest that older patients and females are less likely to receive an intensive treatment than younger and male patients.

In order to declare that such observed differences are indeed associated with sex and age, we must be sure that there is not another source from which the observed differences in treatment stem, in particular those related to medical indication for the treatment of patients. As such, we conducted a Disease Staging classification which allowed us to control for the severity of illness of patients. We also used in this study a set of control variables that capture other characteristics of patients and also hospitals, some of them with statistical significance. But even with such controls, there remain differences in the degree of treatment intensivity that sex and age of patients seem to explain.

Despite the probable connotation of such findings with prejudice issues, we are reluctant to declare that these results reflect phenomena of pure prejudice or bias towards patients on the basis of gender and age. According to the theoretical model of Balsa and McGuire (2003), sex and age based disparities in health care can be caused by several possible mechanisms, being prejudice and rational profiling of patients the two alternatives explored above. Nevertheless, as shown, although these two mechanisms are radically different from a sociologic and moral point of view, both can generate an unfair allocation of medical treatment across patient groups. As pointed by Balsa and McGuire (2003), the distinction between disparities caused by prejudice and by lack of information is particularly relevant from a policy point of view. If disparities are caused by prejudice, there is the need for regulation on medical professionals. Otherwise, if disparities are caused by rational profiling in face of clinical uncertainty, attention must be directed to policies to improve information and the inference procedure made by

doctors. Though scarce, there are some empirical works that try to measure the magnitude and the importance of these different sources of disparities.

Because literature documenting disparities based on social group of patients seldom explores the welfare implications of such disparities, we also present a quantification of the consequences of the disparities found between the treatment given to men and women. Adopting a methodology similar to receiver operating characteristics analysis we estimate that 52% of the female patients of our sample were undertreated according to the standard of treatment applied to men, a rate that is 15 percentage points higher than in men. We also observe that undertreated women had a higher probability of death than the correctly not treated.

Finally, we presented an empirical test of statistical discrimination as the underlying mechanism for the discrimination of women in terms of treatment for AMI in Portuguese NHS hospitals. Though we did not test the existence and the magnitude of other sources of discrimination, such as taste-based discrimination, we found that the magnitude of sex based discrimination in AMI treatment depends on if the hospital was subject to a corporatization shift by which financial and performance incentives were imposed to some NHS hospitals in Portugal. We interpret this as evidence compatible with statistical discrimination.

Concerning our econometric procedures, we must acknowledge that there are a number of patient characteristics that would be important to control in order to increase the robustness of the results (e.g., race, socioeconomic status, health status and history). However, data on such characteristics unfortunately is not available in the registry of episodes of inpatient and outpatient surgeries in NHS hospitals maintained by the Portuguese Government.

Appendix 1

Here we present the Rogers (1993) approach to correct standard errors for intra-cluster correlation. Although this is a generic method, for the sake of simplicity of the demonstration we apply it in the case of linear regression, drawing mainly on the notation of Primo et al. (2007).

The variance-covariance matrix for linear regression takes the form $\text{var}(\beta) = E[(X'X)^{-1}X'\epsilon\epsilon'X(X'X)^{-1}]$. The traditional OLS assumption is that $E[\epsilon\epsilon'] = \sigma^2\mathbf{I}$, where σ^2 is the average of the square residuals. Thus, the variance-covariance matrix for OLS is $\text{var}_{\text{OLS}}(\beta) = \sigma^2(X'X)^{-1}$, which has all diagonal terms identical and all off-diagonal terms equal to zero.

This means that to conduct valid statistical inference, OLS requires (as most estimation methods do) that the error term is independent and identically distributed (i.i.d.) across observations. But when the structure of the data is such that some observations are correlated to others because they share some common, even if unmeasurable, characteristics, the i.i.d. assumption is violated. As a result of such clustering of observations, OLS standard errors are typically underestimated, thus invalidating statistical inference.

Following Rogers (1993), in order to take into account such intra-cluster correlation of observations, we must assume that observations from different clusters are independent but correlated within the same cluster. In terms of the variance-covariance matrix, this means that we do not assume that the diagonal terms are identical and also we do not assume off-diagonal terms are zero unless they come from different clusters. Hence, $E[\epsilon\epsilon']$ is no longer equal to $\sigma^2\mathbf{I}$. Now, $E[\epsilon\epsilon']$ consists of individual-specific variances along the diagonal and covariances of errors on the off-diagonals, which can be non-zero for observations from the same cluster.

Thus, letting $i = 1, \dots, N$ index individuals, $j = 1, \dots, J$ index clusters to which individuals belong and n_j be the number of observations in cluster j , the cluster adjusted variance-covariance matrix is given by

$$\text{var}_{\text{CLUST}}(\boldsymbol{\beta}) = (\mathbf{X}'\mathbf{X})^{-1} \sum_{j=1}^J \left\{ \left(\sum_{i=1}^{n_j} \hat{\boldsymbol{\varepsilon}}_i \mathbf{X}_i \right) \left(\sum_{i=1}^{n_j} \hat{\boldsymbol{\varepsilon}}_i \mathbf{X}_i \right)' \right\} (\mathbf{X}'\mathbf{X})^{-1}, \quad \text{where } \mathbf{X}_i \text{ refers to the}$$

observations within a given cluster.

For the formalization of the estimator of the variance-covariance matrix for logistic regression with intra-cluster correlation, as well as additional considerations relating to large and small sample behaviour of the estimator, see Wooldridge (2006) and Cameron and Trivedi (2009).

Appendix 2

Table A2.1: Estimation results of the probit regression model for the probability of patients with AMI receiving intensive treatment

Variable	Coefs.	Z-stat Rogers	AME	MEM
sexi	-0.241	(10.82)***	-0.070	-0.080
agei	-0.029	(29.69)***	-0.008	-0.010
fini	-0.131	(2.06)**	-0.038	-0.043
stagei	-0.008	(2.20)**	-0.002	-0.003
cvs10i	-0.268	(7.41)***	-0.078	-0.089
centrj	0.797	(2.66)***	0.231	0.264
distj	0.481	(1.86)*	0.139	0.159
epej	-0.022	(0.19)	-0.006	-0.007
univj	-0.143	(0.77)	-0.041	-0.047
especj	0.502	(2.45)**	0.145	0.166
medicj	0.013	(2.08)**	0.004	0.004
y2001	0.175	(4.06)***	0.051	0.058
y2002	0.324	(6.44)***	0.094	0.107
y2003	0.473	(5.57)***	0.137	0.156
y2004	0.627	(5.04)***	0.182	0.208
y2005	0.728	(5.36)***	0.211	0.241
y2006	0.881	(6.23)***	0.255	0.291
y2007	0.926	(6.03)***	0.268	0.306
y2008	0.991	(6.10)***	0.287	0.328
Constant	0.241	(0.87)	-	-

Observations: 89,026
 Absolute value of z statistics in parentheses
 * significant at 10%; ** significant at 5%; *** significant at 1%
 Pseudo $R^2 = 0.1609$
 Prob>chi² = 0.0000

Table A2.2: Estimation results of the linear probability regression model for the probability of patients with AMI receiving intensive treatment

Variable	Coefs.	Z-stat Rogers	AME	MEM
sexi	-0.066	(8.03)***	-0.066	-0.066
agei	-0.009	(18.56)***	-0.009	-0.009
fini	-0.038	(2.06)**	-0.038	-0.038
stagei	-0.002	(2.12)**	-0.002	-0.002
cvs10i	-0.092	(7.64)***	-0.092	-0.092
centrj	0.161	(2.55)**	0.161	0.161
distj	0.068	(1.75)*	0.068	0.068
epej	-0.007	(0.18)	-0.007	-0.007
univj	-0.036	(0.64)	-0.036	-0.036
especj	0.190	(3.03)***	0.190	0.190
medicj	0.004	(2.12)**	0.004	0.004
y2001	0.041	(4.80)***	0.041	0.041
y2002	0.078	(7.74)***	0.078	0.078
y2003	0.120	(6.02)***	0.120	0.120
y2004	0.165	(5.25)***	0.165	0.165
y2005	0.196	(5.79)***	0.196	0.196
y2006	0.244	(6.80)***	0.244	0.244
y2007	0.258	(6.37)***	0.258	0.258
y2008	0.281	(6.57)***	0.281	0.281
Constant	0.665	(11.78)***	-	-

Observations: 89,026
 Absolute value of z statistics in parentheses
 * significant at 10%; ** significant at 5%; *** significant at 1%
 Pseudo $R^2 = 0.1835$
 Prob>chi² = 0.0000

Appendix 3

Table A3.1: Estimation results of the logistic regression model for the probability of patients with AMI receiving intensive treatment, with interaction term between age and sex

Variable	Coefs.	Z-stat Rogers	Odds-Ratios
sexi	-0.418	(10.88)***	0.658
agei	-0.047	(28.87)***	0.955
agei*sexi	-0.009	(3.72)***	0.991
fini	-0.219	(2.06)**	0.804
stagei	-0.013	(2.16)**	0.987
cvs10i	-0.469	(7.80)***	0.626
centrj	1.415	(2.54)**	4.118
distj	0.883	(1.77)*	2.418
epej	-0.039	(0.19)	0.962
univj	-0.221	(0.71)	0.802
especj	0.857	(2.49)**	2.357
medicj	0.021	(2.00)**	1.022
y2001	0.308	(4.02)***	1.361
y2002	0.560	(6.24)***	1.750
y2003	0.815	(5.55)***	2.259
y2004	1.080	(5.05)***	2.943
y2005	1.248	(5.29)***	3.484
y2006	1.506	(6.13)***	4.509
y2007	1.584	(5.94)***	4.873
y2008	1.691	(6.01)***	5.426
Constant	-3.019	(5.94)***	-

Observations: 89,026

Absolute value of z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

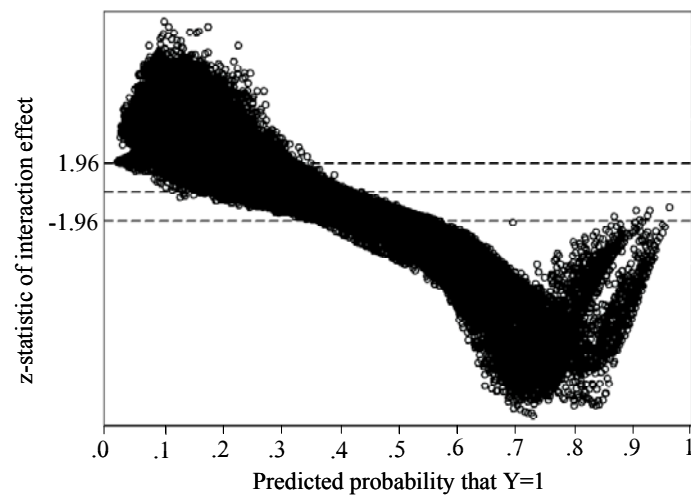
Pseudo $R^2 = 0.1599$

Prob>chi² = 0.0000

Table A3.2: Statistics of interaction effects between sex and age

	Mean	Std. Dev.	Min	Max
Interaction effect	-0.0002	0.0014	-0.0040	0.0021
Standard error	0.0005	0.0002	0.0001	0.0013
z-statistic	0.3386	3.9594	-15.4854	11.7990

Figure A3: Z-statistics of interaction effects after logit estimation



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ESSAY 3

Hospitalization of Ambulatory Care Sensitive Conditions and Access to Primary Care in Portugal

Abstract

We analyze small area variation in hospitalization rates for Ambulatory Care Sensitive Condition (ACSC) with a framework that allows us to explicitly address and describe barriers faced by patients when accessing services. Our empirical application examines data of hospitalizations in public hospitals and characteristics of the public primary care delivery system in small areas of Portugal in 2007. Though data on specific access barriers is scarce, results show that a model with access variables explains 60% of the variation in ACSC hospitalization rates, 12 percentage points more than a model without such variables. Our results also shed some light on the relative importance of access barriers. Increasing resources does not seem to necessarily enhance patient access to care. Other factors, such as reduced travel time and long term patient-doctor ties, arise as more important in reducing unnecessary hospitalizations.

Hospitalization of Ambulatory Care Sensitive Conditions and Access to Primary Care in Portugal

César Carneiro
cesar.carneiro@portugalmail.pt

1. Introduction

As defined by Billings et al. (1993), Ambulatory Care Sensitive Conditions (ACSC) are medical conditions for which timely and appropriate outpatient or ambulatory care can help reduce the risk of hospitalization by either preventing the onset of an illness or condition, controlling an acute episodic illness or condition, or managing a chronic disease or condition.

At least since 1993, the rate of admissions to hospitals for ACSC has been used as an indicator of access to primary care. The rationale behind it is that if there is an effective and accessible system of primary care, then most ACSC will be prevented or managed in primary outpatient care, thus avoiding the need for hospitalization. On the opposite side, a lack of timely and effective primary care will determine a higher rate of hospitalization of such conditions. From a normative point of view, one can classify hospitalization of ACSC as unnecessary hospitalizations.

Most studies on hospitalization of ACSC take small geographic areas as the unit of analysis, an approach termed ‘small area analysis’. Such analysis consists of evaluating variations in utilization of health care in small geographic or demographic areas. By comparing high and low-use areas, it attempts to determine whether there is a pattern to such use and to identify variables that are associated with and contribute to the variations.

The rise of small area analysis in health services research, and more specifically, in the study of health care utilization, comes mostly from the fact that several studies document large variations in rates of hospitalization among nations, regions, states, communities, and neighbourhoods. Even though variations in small areas have been, for several years, a phenomenon that captures the interest of many economists, it remains largely a topic of discussion. Simply put by Phelps (1995), the literature on this topic

has shown that a person's chances of receiving a particular medical intervention depend heavily on geographic location, even after holding constant factors normally considered as affecting demand for medical treatment. The focus on assessments of access and quality of care for populations and not just for specific patients, mainly for public policy purposes, immediately linked the research on ACSC to small area analysis.

The seminal work of Billings et al. (1993) focused on explaining variations in rates of hospitalization in small areas of New York City (zip code areas) through differences in socioeconomic status. They aimed to determine whether small area analysis might become a useful tool for assessing barriers to outpatient care and for evaluating the effectiveness of programs designed to improve access to care. Their findings suggested that lack of timely and effective outpatient care may lead to higher hospitalization rates in low-income areas, and that hospitalization rates of ACSC were higher in low-income areas than they were in higher-income areas where appropriate outpatient care was more readily available. On another setting (Valencia, in Spain), however, Casanova et al. (1996) found that socioeconomic variables, type of physician or a previous visit to primary care services were not associated with a different risk of hospitalization due to ACSC. Therefore, there isn't a consensus on the factors that influence the geographic variations in rates of ACSC hospitalizations. The observation that such influence is sensitive to the particular setting being analyzed suggests the existence of other relevant factors not taken into account.

Studies on hospitalization of ACSC taking the patient as the unit of analysis rather than small areas, though less numerous, also exist. For example, Shi et al. (1999) examined patient sociodemographic characteristics associated with hospitalizations for ACSC in South Carolina, United States (US), during 1995. They found that nonwhites, low income individuals and individuals residing in more rural areas had significantly more ACSC hospitalizations than their respective counterparts, and also that individuals without a primary care physician were more likely to be hospitalized with ACSC.

Since the original work of Billings et al. (1993), hospitalization rates for ACSC have gained wide acceptance as indicators for policy choices in the US. Because the connections between access, the supply of clinicians, and ACSC rates were often assumed to be tight and logical, the most common policy reaction to any conclusion that

parts of the US lacked access to primary health care was to redirect resources, most often physicians or federally supported clinics.

In that line, subsequent analyses of ACSC rates, conducted to test their ability to identify underserved areas, used the supply of primary care health facilities or professionals as the measure of potential access for the small areas being examined (Bindman et al., 1995; Grumbach et al., 1997; Schreiber and Zielinski, 1997; Lambrew et al., 1996; Ansari et al., 2003).

As mentioned by Ricketts et al. (2001), the research on hospitalization rates for ACSC is based on the assumption that ACSC rates reliably correlate with deficiencies in primary care access for geographic areas. However, their finding that rates of hospitalization for ACSC in small areas are poorly correlated with the existence of primary care resources confirms that access to effective health care is a function of more than the availability of resources. As Billings et al. (1993) had already recognized, in the research on ACSC rates, barriers to access remain something of a “black box,” and further research is required to identify the relative impact of the economic, structural, and cultural factors that affect access to care.

A multivariate analysis on respondents to the 1987 National Medical Expenditure survey in the US revealed no correlation between having an ACSC admission and having a regular source of care, which is a common and simplified measure of access to health care (Lambrew et al. 1996).

Schreiber and Zielinski (1997) found that the number of physicians per population is positively associated with ACSC admissions, which is contrary to what would be expected if ACSC rates reflected shortages of primary care capacity. They suggested that high ACSC admissions may be a reflection of deficits in primary care availability, accessibility or appropriateness, and that in-depth study was needed to determine the relative importance of these factors in a given geographical area.

Another string of literature tries to reveal what’s inside the “black box”, by studying factors influencing access to health care. Before the 1980’s, most studies of access to health care were either based on the utilization of health services as the main indicator

of access, or centred on basic characteristics of the delivery system, such as doctor-to-patient ratios. A new perspective was introduced by Penchansky and Thomas (1981), putting the focus on the process of access, in order to be able to define and measure the phenomena that influence the use of health care services. They define access to health care as the fit between consumer needs and the delivery system, grouping barriers to access into five independent dimensions.

This work has two main objectives: first, to combine both the approach of ACSC rates and the Penchansky and Thomas (1981) framework of access, building a tool for analysing variations in small areas and assessing barriers to access for primary health care; second, to explicitly address and describe some of those barriers, through an empirical test of the relevance on ACSC hospitalization rates of factors that can be grouped in the access dimensions of that framework.

Our study examines data of hospitalizations in public hospitals and characteristics of the public primary care delivery system in small areas of Portugal in 2007. Though data on specific access barriers is scarce, results show that a model with access variables explains 60% of the variation in ACSC hospitalization rates, 12 percentage points more than a model without such variables. Our results also shed some light on the relative importance of access barriers. Increasing resources does not seem to necessarily enhance patient access to care. Other factors, such as reduced travel time and long term patient-doctor ties arise as more important in reducing unnecessary hospitalizations.

This paper is organized as follows: on section 2 we present a framework for the study of access to health care based on a model of demand for health care; on section 3 we present an empirical analysis of the relationship between ACSC hospitalization rates and key access factors, describing the methods, variables and data used and finally the results of our empirical work; and on section 4 we discuss the main conclusions and policy implications of our findings.

2. A model of access to health care

2.1. Background

Andersen and Newman (1973) and Aday and Andersen (1974) conceptualized access as resulting from both characteristics of the population and of the delivery system, and considered that “appropriate” utilization was the key indicator of access.

Penchansky and Thomas (1981), in turn, put the focus on the process of access, in order to be able to define and measure the phenomena that influence the use of health care services. They define access to health care as the fit between consumer needs and the delivery system, i.e., the degree to which the health care system facilitates or inhibits consumers to enter the system and receive services. This fit is influenced by the existence of several barriers to access, which they group into five independent dimensions: availability, accessibility, affordability, accommodation and acceptability.

As Ricketts and Goldsmith (2005) summarized, Aday and Andersen (1974) and Penchansky and Thomas (1981) have established two alternative theoretical approaches for the study of access to medical care, respectively “access as use” and “access as fit”.

The literature that followed Penchansky and Thomas (1981) is mainly theoretical, and focused on correctly defining, delimiting and extending the five dimensions of access (Berk and Schur, 1998; Goddard and Smith, 2001; Slack et al., 2002; Travassos and Martins, 2004; Ricketts and Goldsmith, 2005). In terms of methodology issues, the literature that adopts this concept of access is divided in two blocks: the measurement of the geographic dimensions, accessibility and availability, consisting mainly in applying Geographic Information Systems (GIS) methods; and the measurement of non-geographic dimensions, affordability, acceptability and accommodation, on which research is sparser and mainly based on survey studies to collect opinions of users.

However, the Aday and Andersen’s framework (1974) has been used to guide empirical research and evaluation studies on access more often than the “fit” approach of Penchansky and Thomas, which means that the merits of the latter in addressing specific issues of the process of access are often ignored in the research on access to health care.

More important, it seems to exist a clear separation between the literature on access to health care and the literature on the determinants of demand for health care. The latter seldom accounts for issues of fit and restrictions on utilization imposed by characteristics of the delivery system, rather focusing on individual characteristics of health care users. As a result, more than thirty years have passed since the work of Aday and Andersen (1974) and we still cannot find in the literature a comprehensive, precise and fully usable framework that can guide empirical research on access to health care.

2.2. The model

In the spirit of Penchansky and Thomas (1981), we consider that the mere existence of demand and supply of health care does not guarantee that utilization of services will occur, or that consumers are fully satisfied with the services they get. Access to health care will depend on the degree of fit between the clients and the system characteristics.

On the other hand, we follow Aday and Andersen (1974) in the sense that we consider that characteristics of the system and of the population influence whether entry is gained, but the proof of access is not the mere availability of services and resources but whether they are actually utilized by the people who seek them.

Thus, we assume that the outcome of access is the consequence of the existence of demand and supply, but also that it depends on the degree of fit between the delivery system and the demand, i.e., how the characteristics of the health care delivery system influence the degree to which that system facilitates or inhibits consumers to receive services.

We model the individual decision in the spirit of the Cameron et al. (1988) model of demand for health care, in a simple single period context, but we explicitly take account for fit between preferences of consumers and system characteristics.

Consider the existence of J providers of health care and let v_{ij} denote the number of visits made by individual i to provider j (e.g., visits to doctors), where $j = 1, \dots, J$. Let C_i be the quantity consumed of other goods and H_i a stock of health measured as

income equivalent. $H_i = h\left(\sum_{j=1}^J v_{ij} \mid \mathbf{X}_i, \varepsilon_i, \mathbf{F}_{ij}\right)$ is a health production function that depends on the consumption of medical care, conditional on a random health shock ε_i , a vector of individual characteristics $\mathbf{X}_i$ (consumer attributes) and a vector $\mathbf{F}_{ij}$ of choice-specific variables which reflects the fit between the preferences of consumer i and provider j characteristics. For simplicity, we assume that the probability distribution for ε_i is unconditional (denoted by $P(\varepsilon_i)$).¹

The consumer maximizes the utility function $U(C_i, H_i)$ choosing the quantities of C_i and v_{ij} , subject to a budget constraint given by the income of the individual Y_i and the prices of C (P_C) and v in provider j (Pv_j). As usual, U and H are both increasing in their arguments.

Summarizing, consumer i solves the following optimization problem:

$$\underset{\{C_i, v_{ij}, \dots, v_{iJ}\}}{\text{Max}} U(C_i, H_i) \text{ s.t. } \begin{cases} H_i = h\left(\sum_{j=1}^J v_{ij} \mid \mathbf{X}_i, \varepsilon_i, \mathbf{F}_{ij}\right) \\ Y_i = C_i \times P_C + \sum_{j=1}^J v_{ij} P v_j \\ P(\varepsilon_i) \\ v_{ij} \in \mathbb{N} \end{cases}$$

Therefore, the demand function for visits of patient i to provider j is $v_{ij} = v(\mathbf{X}_i, \hat{\varepsilon}_i, Y_i, P v_j, \dots, P v_J, \mathbf{F}_{ij})$, where $\hat{\varepsilon}_i$ is the realized health shock. In this demand function we have all features of our framework for the study of access to health care: patient characteristics and income, need for health care, prices of services and the provider characteristics that influence fit.

The component $\mathbf{F}_{ij}$ can be seen as a measure of quality of services offered by the supplier j as perceived by patient i , that comprises all characteristics of that provider that facilitate or inhibit consumers to accede to it and receive services. As we already

¹ Some literature on health care demand models realistically assumes a probability distribution for the random health shock conditional on patient characteristics, an assumption that raises endogeneity issues (see Vera-Hernández, 1999).

mentioned, Penchansky and Thomas (1981) group barriers to access into five independent dimensions: availability, accessibility, affordability, accommodation and acceptability. Availability and accessibility are the two geographic dimensions of access, and are defined as the adequacy of the supply of health care, in terms of volume and type of services, and the relationship between the location of supply and the location of clients, in terms of transportation resources, distance, travel time and cost, respectively. Affordability relates to the prices of health services and the financial ability of clients to pay for those services; accommodation is the relationship between the organization of the services to accept clients (in terms of appointment systems, hours of operation, walk-in facilities, etc.) and the client's ability to accommodate to that organization; and finally, acceptability represents the attitudes of clients about personal and practice characteristics of providers (age, sex, ethnicity, type of facility, religious affiliation, etc.), and the providers attitudes about clients personal characteristics.

In our model F_{ij} will not include characteristics of affordability as defined by Penchansky and Thomas (1981). The affordability dimension results of factors from both patient and provider side, since it relates to the prices of health services and the financial ability of clients to pay for those services. The model laid down in this section accounts for such interaction by considering explicitly the price of services in providers $j = 1, \dots, J$ and the income of patient i .

One final note on the availability dimension is in order. Notice that the model implies that there is always some available provider, since v_{ij} can only be null due to the decision of the consumer. However, this doesn't mean that we are assuming that services will be always supplied in sufficient quantities without imposing any restriction on access. We predict that, assuming the existence of providers, any availability restrictions, in terms of volume of services offered, must be reflected in other observed aspects of the framework, such as waiting times or travel distance (e.g., if hospitals are scarce in some region, people will have to travel longer distances and will have longer waiting times in the existing hospitals). In fact, as some of the literature already cited argues, there is evidence that the existence of supply of services alone does not predict the utilization of care by people who need it, a finding that indicates that issues of fit

must play an important role in the process of entry to system and utilization of care. An example is Wan and Soifer (1974), who concluded that doctor-to-population ratios are not always significant in predicting utilization. In that perspective, if our prediction proves correct, we can exclude from our model an explicit measure of availability of services, rather capturing eventual effects of scarcity of supply of services in other dimensions of $\mathbf{F}_{ij}$.

By reconciling both Aday and Andersen (1974) and Penchansky and Thomas (1981) frameworks, nesting them in a usable health care demand model, we are able to describe those factors that inhibit or facilitate entrance to the health care delivery system and how they operate, and more important, how they can be affected by policy measures to increase access to health care.

3. Empirical analysis of ACSC rates

Objective and study design

Our aim is to study the relationship between the incidence of hospitalizations of ACSC in small areas and characteristics of the primary care delivery system that are associated with access to care. Therefore, the unit of analysis is the geographic aggregate, or as designated in literature, small area.

Following Penchansky and Thomas (1981), in this study we consider the availability, accessibility and acceptability dimensions of access, which are defined, respectively, as the adequacy of the supply of health care, in terms of volume and type of services, the relationship between the location of supply and the location of clients, in terms of transportation resources, distance, travel time and cost, and the mutual acceptance of patient and provider characteristics. Notice that in the model presented in the previous section we predicted that the availability effect must be captured by other dimensions of fit, which would allow us to exclude explicit measures of the supply of services. We will address again this issue when we interpret the results of the empirical analysis.

We dropped the affordability dimension of access because in the particular setting that we study – public primary health care in Portugal – it is not relevant. As we explain in the following section, price of services equals the same small amount at every point of service. For the same reason, here individual income will not play the role of an enabling factor in the traditional fashion, but as we will see latter, it will be considered for its implications on the possibility to accede to private care. As for the accommodation dimension, it was not considered in our empirical analysis due to unavailability of relevant data on the subject.

Each of the three studied dimensions is related to different, but often complementary, perspectives of how to reduce inequities in access to health care. On the perspective of availability, access to care can be improved by redirecting resources, namely professionals, to the unfavoured areas, whereas on the perspective of accessibility, access can be improved by reducing the geographic distance of populations to the points of delivery. Finally, acceptability is related to factors than influence the degree of satisfaction enjoyed both by service users and professionals. On this perspective, increasing access to care may be achieved through careful matching of the characteristics of provider professionals and facilities to the personal characteristics and preferences of populations being served (these characteristics can be, for instance, race, sex, ethnicity, language).

We also take into account several control variables that intend to capture population specific characteristics that, according to most literature on ACSC, influence the rate of hospitalization of these conditions. These are mostly socioeconomic status and demographic variables.

A multivariate relationship of such key access variables and control variables to the ACSC hospitalization rates was estimated using a linear regression model. A previous analysis of the distribution of the dependent variable, consisting of a distributional plot and an empirical distribution test, did not provide evidence to reject the assumption of a standard normal distribution. Thus, we estimated the model by Ordinary Least Squares (OLS).

Setting

Publicly funded primary care in Portugal is almost exclusively delivered in National Health Service (NHS) clinics with state employed general practitioners (GP's).² These clinics, called Health Centres, offer primary care consultations and basic ambulatory nursing services to all Portuguese residents. In some Centres there are specialist consultations, but these have a much lower weight on the bulk of services offered. The network of Centres covers all mainland territory of Portugal,³ and, beside some exceptions, it is identified with municipalities. That is, all 278 Portuguese continental municipalities have at least one primary care centre and several extensions, and some urban municipalities have more than one centre. Though being legally consecrated the principle of liberty of choice of Health Centre, the rule followed by the authorities is to allocate NHS beneficiaries (which include all Portuguese population and also legal immigrants) to the Centre of the municipality where they reside. Thus, municipalities are geographic areas that reflect primary care service areas, and for that reason, that is the natural matrix of small areas to be considered in our analysis.

We aggregate data on resources of primary care at the municipality level and consider all geographic points of delivery within a municipality in the accessibility measurement of that area.

Dependent variable

The dependent variable of our study consists of the number of ACSC episodes of residents of a small area per thousand residents of that area (this variable was denoted by **acsadmisrate**). Diagnoses were classified as ACSC and non-ACSC using the list of ICD-9-CM codes applied by Billings et al. (1993) for analyzing hospital use patterns. This list was developed by a medical advisory panel of internists and paediatricians, including experts on access barriers. Using a modified Delphi approach, the panel defined a list of conditions-diagnoses for which timely and effective outpatient care can help to reduce the risks of hospitalization. This same list of conditions – or a reviewed

² Some state employees have a second layer of public financial coverage of health care expenditures (the ADSE subsystem), which allows them to attend to GP consultations outside the NHS. However, they represent a small fraction of the population.

³ We exclude from the analysis the portuguese islands, Madeira and Azores, because they have autonomous health systems, independent of the NHS.

version of it – was latter used by several authors, including Schreiber and Zielinski (1997), Shi et al. (1999), Parchman and Culler (1999), McCall et al. (2001) and Roos et al. (2005).

Access variables

As explained on the ‘objective and study design’ section, our aim is to examine the relationship between hospital admission rates of ACSC and three primary care access dimensions: availability of resources, geographic accessibility and acceptability by patients. Thus, we defined three independent variables as policy variables (those whose effects we are concerned about).

As a measure of the supply of resources we consider the number of public GP’s per thousand residents of small area (**pubgpperthous**). This ratio, and other similar ones, is a common indicator of availability of health care resources, particularly suitable for analyses of access to primary care, since labour is the main productive input in this type of service. It is used as a measure of supply by several authors including Ricketts et al. (2001), Parchman and Culler (1994), Schreiber and Zielinski (1997) and Ansari et al. (2003).

The geographic accessibility in each municipality was defined as the average travel time from any point in that municipality to the closest point of delivery. Since it was unfeasible to georeferenciate every location of residence, we computed the following approximate indicator. For each municipality, we calculated the travel time from every *freguesia* (which are administrative subdivisions of municipalities) to the *freguesia* where the closest point of delivery is located, and computed a weighted average of those travel times, using the ratios of resident population on the total population of the municipality as weights (**traveltime**).⁴ This information was computed with a Geographic Information Systems (GIS) software, based on data of resident population in 2007, the network of Health Centres and extensions in 2007 and the road network in 2006.

⁴ *Freguesias* are the smallest administrative units in Portugal and also the smallest geographic units we where able to georeferenciate. There are currently 4077 *freguesias* in mainland territory of Portugal. We used the geographic centroid of each *freguesia* to calculate the distances.

To capture an element of acceptability we considered the proportion of population with a NHS family physician (**famphys**). To understand the relevance of this variable, additional description of how publicly funded primary care is provided in Portugal is in order. In principle, every user of Health Centres is entitled to have a family physician, who generally is a GP who assumes the role of regular doctor to every individual of a family. This type of enrolment aims at creating a relationship between patients and doctors built on trust and comfort to patients, in order to reduce switching costs that arise if users frequently have to recur to different doctors.⁵ However, in practice, due to shortage of medical professionals in Health Centres, or in some cases, to organizational problems, some users cannot have a family doctor. Every time these users seek care in Health Centres, they have a different doctor, thus not benefiting from the same advantages of having a long term relationship with the doctor as users with family doctor. In that sense, we assume that having a family doctor improves the satisfaction of users, and thus, facilitates access to care. In deed, some research on rates of hospitalization of ACSC found that having a regular primary care physician is associated with less probability of hospitalizations due to these conditions (Shi et al., 1999; Parchman and Culler, 1994), and Weiss and Blustein (1996) found evidence that Americans with long-standing ties with their physicians are less likely to have hospitalizations. Hence that the variables **pubgppperthous** and **famphys** do not have the same meaning, since the first one indicates the availability of doctors in Health Centres relatively to the population size and the second describes the organizational feature of creating ties between doctors and patients. Though some correlation between the two would be expected in theory, we observe in our data that the variables are poorly correlated (0.20), thus indicating considerable heterogeneity in terms of organizational characteristics between NHS Health Centres.

Control variables

We considered a group of control variables in order to aggregately capture individual sociodemographic characteristics that may influence the rate of hospitalization of ACSC.

⁵ On the relevance of switching costs in health care see, for example, Weiss and Blustein (1996), Thomas et al. (1995) and Grytten and Sørensen (2000). Though certainly interesting, further discussion on this theme is not in the scope of this paper.

According to some literature on ACSC, low income individuals are more likely to be hospitalized with ACSC (Billings et al. 1993; Shi et al., 1999; Ricketts et al., 2001; Ansari et al., 2003; Roos et al., 2005). Thus we controlled the analysis for the average monthly income of small areas (**income**). As we mentioned earlier, since price of services is not relevant in the setting we study, income is not considered here for its impact in the ability of clients to pay for those services. However, we considered income also for its implications on the possibility to accede to private care alternatives to NHS Health Centres. In fact, in some particular cases, evidence suggests that utilization of certain types of care is negatively correlated with socioeconomic status. For instance, Propper (2000) observed that being employed and having high income are negatively associated with use of public care, but positively associated with use of private care.

Another often cited characteristic that appears to be associated with the rate of preventable hospitalizations is gender. Shi et al. (1999) found that female adults were more likely to be admitted for ACSC than male adults, and Parchman and Culler (1999) present similar findings. In our geographic aggregated analysis we controlled for gender through the percentage of female residents of small areas (**sexfem**).

As pointed by Billings et al. (1993), for many chronic diseases such as asthma or diabetes, patient education on outpatient management of the condition is essential to maintain effective control of the condition and avoid preventable hospitalizations. Patient ability to learn and comply with self outpatient management is directly influenced by his general level of education. According to the results of Ansari et al. (2003), ACSC rates are higher in regions with lower levels of education, and Parchman and Culler (1999) present evidence that suggests that individuals with more education than high school are less likely to be admitted due to ACSC. Therefore, we also controlled for the gross rate of education at high-school level of small areas (**education**), computed as the number of residents attending high-school on the total number of residents with ages between 15 and 17.

Finally, some authors found that older individuals were more likely to be admitted for ACSC than younger individuals (Parchman and Culler, 1999). However this finding may be sensitive to the particular setting that was analyzed. Most studies use data from

the US, where eligibility to the Medicare system may influence the financial dimension of access, both to outpatient and inpatient care. Some patient level studies exclude from samples individuals aged > 65 to control for such influence, but even in those censored samples there is evidence of positive association between ACSC rates and age (Shi et al., 1993). Accordingly, we controlled the estimation procedure for the percentage of residents aged 65 or higher of small areas (**age65**).

Another kind of more general controls was also considered in the analysis. Similarly to Ricketts et al. (2001), the total hospitalization rate for the small areas was included to adjust for the overall tendency of physicians in each small area to hospitalize (**totadmisratethous**). Additionally, we included the number of private GP's per thousand residents of small areas (**pvtgpperthous**) in order to control for the existence of primary care alternatives to the NHS supply, and also, a dummy variable that takes the value 1 if the small area has a public hospital (**dumpubhosp**), which may affect the ability for populations to accede to hospital care.

Table 1 summarizes all independent variables.

Table 1: Independent variables

Label	Description
<i>Access variables</i>	
travelttime (ACCESSIBILITY)	average travel time from any point in small area to the nearest NHS primary care provider
pubgpperthous (AVAILABILITY)	number of public GP's per 1000 residents of small area
famphys (ACCEPTABILITY)	proportion of residents with a NHS family physician in small area
<i>SES control variables</i>	
income	average monthly income of small area
sexfem	proportion of female residents of small area
education	number of residents attending high-school on total residents aged 15-17 of small area
age65	proportion of residents aged 65 or higher of small area
<i>Other control variables</i>	
totadmisratethous	number of total inpatient episodes of residents of a small area per 1000 residents of that area
pvtgpperthous	number of private GP's per 1000 residents of small area
dumpubhosp	dummy = 1 if small area has NHS hospital

Data description

The data used to compute the ACSC hospitalization rates came from the data base on discharges of all inpatient episodes in Portuguese NHS hospitals in 2007, coded

according to the ICD-9-CM (a total of 1,085,737 episodes), maintained by the Health System Central Administration. Data on primary care resources was collected directly from the five Health Regional Administrations that manage the NHS Health Centres, and the data on private primary care physicians came from the Portuguese Health Regulation Authority data base. The geographic measures (travel times) were computed by the author with a GIS software using information on the locations of the Health Centres and extensions and georeferencing information of *freguesias* from the Portuguese Army Geographic Institute. Finally, sociodemographic data used to compute the control variables came from the Portuguese official statistics agency, the Statistics National Institute.

Of the 1,085,737 hospitalizations in NHS hospitals in Portugal in 2007, 48,117 (4.4%) were for ACSC, according to the Billings et al. (1993) list of ICD-9-CM codes. In table 2 we present the most frequent diagnostics in our sample that are classified as ACSC, which represent close to 70% of the total ACSC hospitalizations. Of the selected list of conditions, bacterial pneumonia was the most frequent, followed by urinary tract infection, acute bronchitis, gastroenteritis and bronchopneumonia.

Table 2: Five most frequent ACSC hospitalizations, 2007

ICD-9-CM Code	Diagnostic description	No. of admissions	Weight in total ACSC admissions
486	Bacterial pneumonia	16979	35.3%
5990	Urinary tract infection	4685	9.7%
4660	Acute bronchitis	4394	9.1%
5589	Gastroenteritis	3849	8.0%
485	Bronchopneumonia	2938	6.1%

Table 3 presents the main sociodemographic characteristics of our sample in terms of micro level data, comparing the profile of patients admitted in hospitals with ACSC versus with non-ACSC. Even without further investigation, some differences are clearly noted between the average profiles of patients of the two types of diagnostics. ACSC hospitalizations are more frequently male patients and are highly concentrated in the lowest (0-14) and highest (65+) age bands (especially in the upper end of the age distribution), when compared to other patients. A large difference can be observed in the average length-of-stay (LOS) of the admissions in favour of ACSC cases, an

indicator which is often considered a proxy of the amount of resources used in inpatient admissions. On average, an ACSC admission has a duration of 8.59 days, which is more than twice the duration of a non-ACSC admission.⁶ Less marked differences appear in the proportion of admissions from the top 25% municipalities in terms of income and in the proportion of individuals with financial coverage exclusively from the NHS.

Table 3: Sociodemographic characteristics of patients hospitalized in Portuguese public hospitals, 2007

Variable	ACSC		Non-ACSC	
	No.	%	No.	%
Total admissions	48117		1037620	
Male	24452	50.82	472480	45.53
Female	23665	49.18	565140	54.47
25% high income Municipalities	18299	38.03	461686	44.49
Age				
0-14	7683	15.97	110449	10.64
15-34	1797	3.73	131287	12.65
35-49	2650	5.51	166737	16.07
50-64	4890	10.16	239876	23.12
65 +	31097	64.63	389271	37.52
NHS coverage	43840	91.11	910869	87.78
Average LOS (in days)	8.59		3.74	

Figure 1 depicts the relative regional distribution of the ACSC admission rates. The map shows a concentration of higher rate areas in rural areas of the north and centre of mainland Portugal, and also relative high rates in the south. A bias to rural areas in the distribution of ACSC rates was also found by Shi et al. (1999), Rickets et al. (2001) and Ansari et al. (2004).

⁶ The same type of difference was found by the Connecticut Office of Health Care Access, although not so expressive. Data from FYs 2000 to 2004 evidenced that ACSC patients had longer average hospital stays than other patients (5.8 days versus 4.8).

Figure 1: ACSC hospital admission rates per 1000 habitants on Portuguese mainland municipalities, 2007



Finally, table 4 presents means and standard deviations of all used variables (except for the dummy variable **dumpubhosp**) in terms of regionally aggregated data.

Table 4: Sample descriptive statistics (N=278)

Variable	Mean	S.D.	Max	Min
acsadmisrate	6.57	4.38	24.09	0.00
pubgpperthous	0.69	0.20	1.91	0.33
traveltime (minutes)	11.1	5.4	35.3	1.0
famphys	0.92	0.10	1.00	0.60
income (euros)	770.0	141.0	1617.9	595.2
sexfem	0.51	0.01	0.55	0.42
education	91.97	41.41	267.90	10.20
age65	0.22	0.06	0.41	0.10
totadmisratethous	125.03	83.90	552.07	0.10
pvtgpperthous	0.18	0.18	1.32	0.00

Estimation results

We estimated two versions of the model, the first one without the access variables and the second one with them, in order to observe the improvement brought by such variables. Taking the adjusted R^2 statistic as a measure of the goodness of fit of the model⁷, we observe that the model with access variables explains 60% of the variation in ACSC hospitalization rates, 12 percentage points more than a model without such variables.

The estimation results of the regression model with access variables (table 5) showed a statistically significant association between the rate of hospitalizations due to ACSC and both travel time and proportion of population with family physicians. Like it was hypothesized, our results suggest that areas with longer average travel times to primary care points of delivery and also areas with a lower proportion of population with a regular family doctor tend to have higher rates of unnecessary hospitalizations. On contrary, the variable that measures supply of resources (number of public GP's per thousand residents) shows an unexpected relationship with ASCS rates – since rates are higher where supply is higher – although with little statistical power.

As we already noted, variables **pubgpperthous** and **famphys** describe distinct characteristics of the provision of primary care in Portuguese NHS Health Centres. The first one is merely a quantitative measure of the availability of resources, and the second one reflects a qualitative organizational aspect which is the extent to which patients are assigned to regular family doctors with whom they are more likely to form long lasting ties. Thus, though some connection can exist between the two variables (since a shortage of doctors can cause a low rate of patients with family physician), they do not necessarily go hand-in-hand, which happens in fact. Not only they show poor Person's correlation, but more importantly, they have a different impact on access to primary care. Our estimation results indicate that attributing a family physician to patients might be more effective in reducing unnecessary hospitalizations than merely augmenting the number of doctors per patient without strengthening patient-doctor ties.

⁷ Adjustment of the R^2 for the model's degrees of freedom is needed here because the unadjusted R^2 statistic can only increase when predictors are added to the regression model.

Table 5 also presents elasticities calculated at the mean of each independent variable, for the model with access variables. As can be seen, the rate of hospitalizations due to ACSC increases 0,237% as the travel time to primary care increases 1% (or an increase of about 24% when travel time doubles), and decreases 0,6% as the proportion of population with family physicians increases 1%.

As for demographic variables, only average income and education level of small areas are statistically relevant, both in the same direction as in most literature: higher income and higher education lead to lower ACSC hospitalization rates.

Our results show no surprises in the estimated coefficients of other control variables, being worthy to note that the supply of private physicians is not statistically correlated with ACSC hospitalization rates.

Table 5: OLS estimates (dependent variable is ACSC hospitalization rates)

	Model without access variables			Model with access variables	
Variable	Estim. Coefs.	t-stat.	Estim. Coefs.	t-stat.	Elast. at mean
<i>Access variables</i>					
pubgpperthous	-	-	1.752	(1.78)*	0.185
traveltime	-	-	0.141	(4.19)***	0.237
famphys	-	-	-4.266	(2.16)**	-0.600
<i>SES control variables</i>					
income	-0.004	(2.93)***	-0.004	(3.15)***	-0.521
sexfem	-3.000	(0.19)	0.863	(0.06)	0.067
education	-0.012	(2.42)**	-0.008	(1.68)*	-0.114
age65	7.058	(1.93)*	4.801	(1.24)	0.161
<i>Other control variables</i>					
totadmisratethous	0.0351	(15.14)***	0.033	(14.61)***	0.635
pvtgpperthous	-0.7056	(0.66)	-0.871	(0.85)	-0.024
dumpubhosp	1.1659	(2.33)**	0.842	(1.73)*	0.029
intercept	6.3991	(0.80)	6.207	(0.81)	-
	N=278		N=278		
	Adjusted R ² =0.48		Adjusted R ² =0.60		

Absolute value of t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

4. Discussion

We combined the approach of ACSC rates and the Penchansky and Thomas (1981) framework of access, building a tool for analysing variations in small areas and assessing barriers to access for primary health care.

Our first conclusion of the empirical application is that variables that capture specific aspects of the process of access to primary health care are relevant in explaining the rate of hospitalizations avoidable by timely primary care. Though such data is scarce, results show that a model with access variables not only explains more than a model without such variables, but also it allows the identification of specific barriers that influence access to health care services. We, therefore, advocate that efforts be made by official authorities in order to collect relevant data on the proposed access dimensions. Such data can relevantly increase the insight of the research, in a way that is useful to design policy measures to increase access to health care.

In line with the findings of studies such as Ricketts et al. (2001) and Schreiber and Zielinski (1997), our results show that more primary care resources does not guarantee less hospitalizations of ACSC. Other measures of access arise as more relevant than availability of primary care resources in explaining variations of rates of unnecessary hospitalizations. In fact, results suggest that geographic accessibility to primary care and having a regular family doctor are more important determinants of rates of hospitalizations for ACSC in small areas. This finding is also in line with our theoretical model of health care demand, where we suppress the availability of services dimension by predicting that any restrictions in terms of volume of services offered must be reflected in other observed aspects of the framework, such as waiting times or travel distance.

Also important, our results support the findings of other research on the relevance of demographics, with areas with low income, older and less educated individuals presenting higher ACSC hospitalizations rates.

The main policy implication of our findings is that given the conditions of the examined setting, increasing patient information and literacy on health needs, increasing spatial

accessibility to points of care and reinforcing stable and long term ties between individuals and family doctors may be more effective in reducing unnecessary hospitalizations than increasing volume of primary care resources. Thus, the solution for increasing access to primary health care and reducing disparities between small areas seems to lie more in organizational changes than in allocation of resources.

Finally, it is worth noting that the importance of reducing unnecessary hospitalizations, though not a subject of our analysis, is supported by our observation that ACSC patients have longer average hospital stays than other patients, and therefore, are most probably more resource consuming hospital admissions.

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