ESSAYS ON THE INFLUENCE OF DOCTORS' SOCIO-DEMOGRAPHIC CHARACTERISTICS ON MEDICAL SPECIALTY ALLOCATION

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Abstract

Medical workforce planning is a key element of any health care system, however factors influencing medical career choice are poorly understood. This thesis contains three essays on the influence of doctors' socio-demographic characteristics on their medical specialty in both the UK and Spain. This thesis aims at understanding the drivers of the occupational segregation between socio-demographic groups, with the objective of helping regulators and policy makers in the design of interventions aimed at reducing the undesired consequences associated with the occupational segregation.

Chapter 2 constitutes a descriptive exercise of the socio-demographic composition of the new cohorts of junior doctors in the UK by analysing their distribution across specialties. The findings show large disparities in that distribution. This chapter provides a discussion of the possible sources of the observed disparities and relates the occupational segregation with the literature on statistical discrimination.

Chapter 3 seeks to disentangle the origins of the outcomes observed in Chapter 2. It develops a conceptual framework that acknowledges the sequential, two-sided nature of the process and that serves as a base for the empirical analysis. The focus of the latter is the estimation of how doctors' socio-demographic characteristics affect their application strategies and specialty choices and selectors' valuations of candidates.

Chapter 4 focuses on the Spanish resident market and explores two of the possible causes leading to the persistent gender gap in surgical specialties. The first focus is on the role of social interactions in shaping doctors' decisions to specialize, more specifically whether female role models constitute an attractor factor for female doctors. The second analyses the functioning of the specialty allocation system and tests whether a policy change has had the unintended consequence of reducing the probability of female doctors accessing highly demanded specialties, including surgical specialties.

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Declaration

I declare that this thesis is a presentation of original work and I am the sole author, except where co-authorship is explicitly acknowledged. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References.

Chapter 2 is written in co-authorship with Professor Martin Chalkley, and has been published as a peer-reviewed research article under the title: *Getting the right balance? A mixed logit analysis of the relationship between UK training doctors' characteristics and their specialties using the 2013 National Training Survey. BMJ Open* 2017; 7(8), e015219. Some revisions and additions have been made for the thesis version. An earlier version of this chapter was presented at the University of York, and at the Spanish Health Economics Association Conference in June 2015 (Granada) and at the Economics of the Healthcare Workforce Conference in July 2015 (Milan). I am the lead author, contributed to the original research idea, prepared the data and carried out the empirical analysis, wrote the first draft, made revisions and disseminated the paper.

Chapter 3 has been presented at the University of York, Universidad de Las Palmas de Gran Canaria, at the European Health Economics Association Conference in July 2016 (Hamburg) and at the Workshop on Labour and Family Economics (WOLFE) in September 2016 (York).

Chapter 4 has been presented at DREAMS Workshop: Widening Access to the Professions in February 2017 (York) and at the Health Economists' Study Group (HESG) in June 2017 (Aberdeen).

Chapter 1

Introduction

This thesis contains three essays on the influence of doctors' socio-demographic characteristics on their medical specialty. The work contained in this thesis contributes to the literature by offering analysis of how the different demographic and socioeconomic groups of junior doctors are sorted across specialties in the UK, and by connecting those differences with statistical discrimination literature (Chapter 2). Having established the existence of large differences between groups, Chapters 3 and 4 seek to disentangle the channels through which those differences arise and are transmitted. Chapter 3 is a sequential analysis of the speciality allocation process in the UK, where we explore how doctors' socio-demographic characteristics can affect their application behaviour and selectors' assessments. Using data from Spain, Chapter 4 examines how social interactions affect decisions to specialise and whether a change in the design of the specialty allocation system can affect female and male doctors differently.

Medical workforce planning is a key element of any health care system. This is largely driven by the time lag existing between the demand and supply of doctors that creates uncertainty and risk. Instructing a doctor is a long and costly process, whereas changes in demand are more sudden (Bloor et al. 2006). Estimates for the average total training cost of a consultant in the UK are over half a million pounds (Netten and Curtis 2016) and these costs are funded out of taxation. Nonetheless, the medical profession is considered elite (Social Mobility and Child Poverty Commission 2014), probably due to the large private human capital investments required and high opportunity costs associated with the long process of becoming a fully trained doctor. The profession shows long run disequilibrium as demand persistently exceeds supply and medical professionals persistently receive rents (Elliott 2003), even when in both Spain and the UK the government is the single largest employer.

The gap between demand and supply in the medical workforce is growing in the UK, one of the main reasons for that being the recent major changes in the composition of the medical workforce (Cleland et al. 2016). Examples of the latter are the feminization of the profession, the increase of the representation of ethnic minority doctors and from those coming from deprived socioeconomic backgrounds, and the large dependence on foreign qualified doctors. Results from Chapter 2 show that, despite the increased representation of these groups, their distribution across specialties and locations is highly unequal. In the case of doctors who graduated overseas this unequal distribution relates to their limited access to specialties, since they can only opt for the training posts that have not been taken in the first round of the specialty allocation process. According to Richards (1994) and Welsh (2000) this differential treatment comes at the risk of creating an underclass of doctors within the NHS. For the other demographic and socioeconomic groups those restrictions do not apply, however factors influencing career choice are poorly understood. Nicholson (2008) defines the three-key elements that determine specialty choice: monetary attributes, non-monetary attributes and doctors' personal characteristics. The monetary and non-monetary attributes of the different specialties are fairly constant over time, which makes it difficult to estimate the impact of those elements on specialty choices using observational data.[1] However, the socio-demographic changes in the composition of the medical workforce and the differential attainment of the new members in the specialty allocation process make further understanding of how doctors' personal characteristics affect their specialty outcomes necessary.

This thesis aims at understanding the drivers of the occupational segregation between socio-demographic groups, and to go beyond the intrinsic preferences justification for those differences. The main objective is to inform policy makers and regulators, and to help them design targeted interventions to aid in the achievement of a balanced distribution of doctors across specialties. From the regulators' perspective, there is a desire to ensure that the medical profession reflects not only appropriate skills but a balance of social, economic, gender and ethnic groups, by promoting a

[1]Trade-off between monetary and non-monetary attributes can be explored through the use of discrete choice experiments as in Sivey et al. (2012) for Australian doctors and Cleland et al. (2016) for the UK, or through the use of surveys as in Spooner et al. (2017).

fair, transparent and effective specialty recruitment process with the objective of being representative of the society it serves (General Medical Council 2010). Moreover, there are several undesired consequences associated with occupational segregation. These include earnings disparities, differences in productivity and in the number of hours worked, shortages of specialists, lower quality of care, and a lower quality of working experience. Arcidiacono and Nicholson (2005) show that the large gender gap in doctors' earnings in the US is connected with their specialty choices. According to Greenaway (2013) difficulties in recruiting for some specialties has resulted in an overdependence on existing or locum doctors to fill rota gaps and, in some cases, has raised patient safety concerns. Blumenthal et al. (2017) compare patient outcomes of locum and non-locum internal medicine doctors finding no differences in 30-days mortality rates between the two groups. However, they find that locums deliver more expensive impatient care and their patients have longer lengths of stay. The authors suggest that locums may struggle to efficiently and effectively deliver care as they lack of institution-specific experience. Regarding doctors' place of qualification Tsugawa, Jena, Orav et al. (2017) show that Medicare patients treated by international graduates had lower risk-adjusted mortality compared with those treated by US graduates. Authors conjecture that better outcomes might be explained by the fact that international doctors are more likely to underwent specialty training twice or that the international group results from a selection of some of the best physicians in their country of origin.

With respect to gender, Bloor et al. (2008) find that male doctors have significantly higher activity rates than females, even after accounting for case mix, and according to Simoens and Hurst (2006) the gap in the number of hours worked between men and women is larger in the UK than in other OECD countries with universal health care systems such as Spain or France. By contrast, Tsugawa, Jena, Figueroa et al. (2017) find that Medicare patients treated by female internists in the US have lower readmission and mortality rates and Wallis et al. (2017) find similar mortality results on elective procedures performed by female surgeons in Canada. In addition, Baumhäkel et al. (2009) find that females are more likely to adhere to clinical guidelines, and Lurie et al. (1993) that they provide preventive care more often. Cooper-Patrick et al. (1999) analyse patients' ratings of their physicians participatory decision making styles and they find that female doctors had more participatory visits with their patients than male doctors, irrespective of their patients' gender. The authors also find that ethnic differences between physicians and patients are often barriers to partnership and effective communication.[2] These findings suggest that a more even distribution of doctors, at least for gender, across specialties could lead to gains in the efficiency of the healthcare system as a whole.

The focus of this thesis is on the supply side of the medical specialty market, more specifically on the causes of the heterogeneous distribution of doctors across specialties. The demand side of the specialty market, i.e. the number of training posts available for each specialty, is fixed and given by the Royal Colleges and Local Education and Training Boards (LETBs) in the UK and by the Ministry of Health in Spain. The analysis of how those quotas are set and how the socio-demographic composition of the new cohorts of doctors may affect them is not considered here. Similarly, and despite geographical location potentially being a relevant element in doctors' decisions to specialise, it only plays a limited role in our analysis due to data and methodological limitations.

Chapters 2 and 3 deal with the specialty allocation process in the UK, whilst Chapter 4 does so for Spain. Both countries have national health systems, although the specialty allocation systems work differently; in the UK the allocation system is two-sided, i.e. doctors apply to specialties, and specialties select doctors from the pool of applicants, whilst in Spain it is one-sided and specialties play a passive role. Nevertheless, both countries present similar problems regarding occupational segregation and the differential attainment of the different socio-demographic groups.

Chapter 2 provides the analysis of the distribution of training doctors across specialties and locations in the UK by means of the National Training Survey (NTS) to quantify evidence of systematic relationships between doctors' socio-demographic characteristics and the specialty and location[3] they are training for. This analysis is innovative in:

- Analysing the NTS that has a very high response rate, hence being a represent-

[2] Authors observe that patients in race-concordant relationships with their physicians rated them as significantly more participatory than patients in race-discordant relationship.

[3] The results for doctors' geographical distribution can be found in the Appendix, see Section 6.1.

ative snapshot of the cohort of doctors in training in the year 2013 who will constitute the medical workforce for many years to come;

- Analysing the role of doctors' socioeconomic backgrounds, that we proxy with the type of secondary school attended, in their specialty allocation outcomes;
- In contrast to previous work in this area, examining imbalances across specialties and locations in both demographic and socioeconomic characteristics simultaneously, and accounting for unobserved heterogeneity by means of a Mixed Logit Model (McFadden and Train 2000);
- Going beyond the differences in preferences between socio-demographic groups and relating the occupational segregation with the literature on statistical discrimination.

The results show substantial differences across specialties. Doctors training in the most demanded specialties are more likely to be male, white, younger, from a better-off socioeconomic background, and to have attended a UK university. What is not clear is whether those differences result from doctors' preferences or are the result of any form of differential attainment in any of the stages of the specialty allocation process. The findings from Chapter 2 open up research questions that are addressed in later chapters of this thesis.

Chapter 3 seeks to understand and disentangle the origins of the outcomes observed in Chapter 2, recognising that the allocation of individuals to specialties is a sequential process. Doctors make decisions as to which specialties to apply for and their applications are then assessed to determine their suitability. At each stage of this process there is selection, either by the doctors themselves or by the selectors reviewing their applications, that might result in specialties becoming unbalanced in terms of social, economic, gender and ethnic characteristics. Thus, the principal objective is to understand how demographic and socioeconomic characteristics impact the different stages of that process. For that purpose, we develop a conceptual framework that serves as a base for the empirical analysis. The data used in this study come from the UK Medical Education Database (UKMED), which collates data on the performance and career progression of the universe of doctors who started their medical studies in the UK in the years 2007 and 2008. This chapter contributes to the literature by:

- Being the first study to comprehensively look at the doctors' application choices and selection outcomes in the context of the multi-stage allocation process and the first to consider comprehensive administrative data for the UK;

- Developing a conceptual framework that describes the functioning of the specialty allocation process in the UK and introduces the element of perceived probability of getting access to a specialty as a decisive element in both application and selection stages;

- Analysing the relationship between an individual's characteristics and their propensity to apply for training in different specialties. We group specialties according to their different attributes: high-income vs. low-income, surgical vs. non-surgical, primary care vs. non-primary care and run-through vs. uncoupled and we estimate by means of a set of Probit regressions how doctors' characteristics can influence their application strategies, controlling for their educational background and previous academic attainment;

- Analysing how doctors' characteristics influence the number of applications that they make. We treat the latter as an indicator of a doctor's own perception of success and also use it as a proxy for doctors' effort in preparing their application(s). That effort is perceived by selectors in the selection stage and allowed to affect specialty selection outcomes;

- Analysing the role of gender and ethnicity in determining interview scores, that is the key element determining selection into specialties, controlling for previous educational attainment by means of a linear regression. We also apply the Oaxaca-Blinder decomposition to the mean interview score to determine what percentage of the observed differences between groups remain unexplained and may be associated with discrimination.

The results for the application stage show that the evidence with respect to selection by doctors in regard to their applications is very strong. The regression results for interview score show that BME doctors and men experience differential attainment in the selection process for specialty training. The results of the Oaxaca-Binder decomposition show that part of the differences in interview score can be explained by the different distribution of observable characteristics between groups, though part of the difference remains unexplained and may be attributable to some form of discrimination. The results regarding the number of applications submitted suggest that, on average, older and ethnic minority doctors are more likely to make more than one application, even after controlling for specialty fixed effects. The results for the selection stage, where the number of applications is used as a proxy for effort, show that the impact of an extra application reduces the interview score, other things being equal.

Chapter 4 focuses on the determinants of gender occupational segregation in the Spanish medical workforce. First, we explore the role of social interactions in shaping doctors' decisions to specialise and we analyse whether being exposed to female role models in male-dominated surgical specialties can affect the specialty choices of female doctors. Second, we analyse the functioning of the specialty allocation system and test whether a policy change in its design has had the unintended consequence of reducing the probability of female doctors accessing highly demanded specialties – a group that encompasses most of the male dominated specialties. Two different data sources are used: a cross-sectional survey that provides doctors' stated preferences regarding their specialty choices and a cross-sectional data set that comes from doctors' administrative records that it is used to identify the doctors who act as role-models and to empirically analyse the consequences of the policy change in the allocation system. This analysis innovates by:

- Being the first study to empirically estimate the effect of informational role models as a determinant of specialty choice, using a survey that provides stated preferences as distinct from revealed specialty choices. This is an advantage as the latter are conditioned by the available choice set at the moment of the specialty choice decision;
- Developing a role model treatment variable that captures the exposure of individuals to female role models in male-dominated specialties;
- Analysing the unintended consequences of a policy change in the specialty allocation process. The change resulted in an increase in the competitiveness of the process and, based on the literature on differential responses to competitiveness

between men and women, we test whether female doctors are worse off after the implementation of the policy.

The findings from Chapter 4 confirm that the observed gender gap in surgical specialties is not only due to differences in intrinsic preferences between men and women. The findings suggest that an increased presence of females in those specialties is an attractor factor for both male and female doctors. Nonetheless, the estimation of social effects is challenging and the existence of other elements that might be correlated with the role model variable and also influencing specialty choices cannot be discarded. With regard to the policy change, the findings suggest that the increase in competitiveness of the process has made female doctors, on average, worse off and, as a consequence, has reduced their probability of accessing the most popular specialties.

Chapter 5 establishes a nexus between the findings of each chapter, drawing policy implications and identifying avenues for future research.

Chapter 2

Getting the right balance? A mixed logit analysis of the relationship between UK training doctors' characteristics and their specialties using the 2013 National Training Survey

2.1 Introduction

The medical profession, with its high rates of return and the associated social prestige, is included in the list of elite or top professions in the UK. Becoming a medical practitioner is a competitive process and represents a substantial investment of time and financial resources, much of that funded through taxation. The profession has been successful in improving access to it for females and ethnic minorities (Milburn 2012), however less so in terms of fostering social mobility as the profession remains dominated by those from better-off socioeconomic backgrounds and little has changed over time (Social Mobility and Child Poverty Commission 2014).

The outcome of the specialty allocation process determines the composition of the medical profession. There is growing concern that the profession should reflect not only appropriate skills but also a balance of social, economic, gender and ethnicity (General Medical Council 2010), to be representative of the society they serve. Achieving a greater balance could improve patient outcomes (Tsugawa, Jena, Figueroa et al. 2017) and foster public health policies targeted at deprived and minority groups (Cohen et al. 2002).

In this chapter, we analyse the distribution of doctors in training in the UK by means of the National Training Survey (NTS) 2013 to quantify evidence of systematic relationships between doctors' socio-demographic characteristics and the specialty they are training for. The NTS is a comprehensive data set that covers all doctors in training and contains information on doctors' socio-demographic characteristics, as well as the specialty and location they are training for. The NTS is a snapshot of the cohort of doctors in training in the year 2013, who will constitute the medical workforce for many years to come. Through the analysis of the outcomes of the specialty allocation process the NTS allows for the identification of disparities and inequities that are present in the current cohorts of doctors in training and, therefore, it can inform policy makers. We consider whether there are imbalances with regard to any one of the demographic or socioeconomic covariates, holding the other characteristics constant, by means of a Mixed Logit model (McFadden and Train 2000). In addition, to the empirical identification of disparities across specialties, we discuss the most probable causes and connect the observed differential attainment to the relevant statistical discrimination literature. The findings of this chapter inform and motivate the analysis in Chapters 3 and 4.

Evidence has been accumulating regarding imbalance in one or more of gender, ethnicity and socioeconomic background across specialties. For example, despite the increase in the number of women entering the medical profession in the last three decades (McKinstry 2008), there exists a large gender difference in the distribution of doctors across specialties (McKinstry 2008; McNally 2008; Lambert et al. 2006; Goldacre et al. 2010) and as a result, women now predominate in paediatrics, obstetrics or general practice, but are the minority in surgery or radiology. Whilst there is no direct evidence regarding the distributions of ethnic and socioeconomic backgrounds across specialties in the UK, studies such as Arulampalam et al. (2005) and McManus et al. (1998) have shown that applicants from disadvantaged and (or) from non-white ethnic backgrounds have less probability of receiving offers from some medical schools, which is an important determinant of specialty allocation (Goldacre et al. 2004). There is also evidence that national and overseas educated doctors have different application patterns (Fazel and Ebmeier 2009) and that overseas educated doctors have restricted access (British Medical Association 2017) to the most popular specialty training posts. This restriction may create an underclass within the NHS (Richards 1994; Welsh 2000).

There is thus a patchwork of evidence indicating that specialties may be unbalanced with regard to the gender, ethnicity and socioeconomic background of their constituent doctors, but no overall view of how these imbalances relate to each other. A fundamental problem is that characteristics such as gender and ethnicity may be correlated, so that an apparent gender imbalance can, in part or in whole, be accounted for by an ethnic imbalance or vice versa.

We find that there are systematic and substantial differences between specialties with respect to training doctors' gender, ethnicity, age, socioeconomic background and country of study. Doctors training in the most demanded specialties,i.e. those specialties with the highest number of applications per training post, are more likely to be male, white, younger, have attended an independent or grammar school, have a parent with tertiary education and have attended a UK university. Our study provides an evidence base for stimulating debate and discussion regarding the possible need to intervene in doctors' training in the UK to redress these imbalances across specialties. A better understanding of how individuals are assigned to specialties is a necessary precondition for the formulation of effective strategies to ensure greater representativeness across medical specialities. In the last two decades, the composition of the medical workforce has changed and now with the feminisation of the medical workforce, the larger dependence on overseas educated doctors, and the desire to widen access to those coming from deprived backgrounds, the need for that knowledge is urgent.

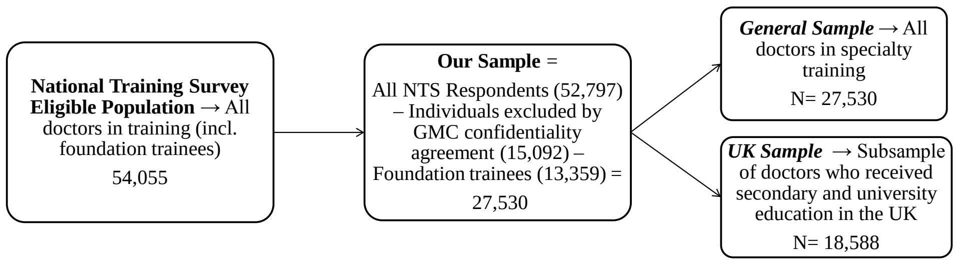
The reminder of the paper is organised as follows: Section 2.2 describes the data and the variables used in the analysis. Section 2.3 describes the econometric model and the empirical implementation. Section 2.4 shows the results from the descriptive statistics and the regression estimates and, finally, Section 2.5 discusses the findings and concludes this chapter. Tables can be found in Section 2.6.

2.2 Data and variables

The General Medical Council (GMC) National Training Survey (NTS) is a cross-sectional survey carried out each year. The survey covers all doctors in training[4] at any one of the UK deaneries or the corresponding Local Education and Training Boards (LETB). From 2013 it has included questions about doctors' socioeconomic background (General Medical Council 2013b). The survey has a high response rate, 97.7% for 2013, which translates to a total of 52,797 responding individuals out of

[4]The General Medical Council (GMC) defines as doctors in training as those who: are in foundation year two; are in a GMC approved LETB/deanery training programme or post; have a fixed term specialty training appointment or have a locum appointment for training.

Figure 2.1: NTS data sampling strategy



54,055 who were eligible for the survey (General Medical Council 2013a). Due to the commitment to confidentiality of the GMC, our study is restricted to individuals who are not unique with respect to the combination of their characteristics and is focused on 40,889 doctors. To establish whether there is probable bias from the omission of some individuals we compared the descriptive statistics for the main demographic and socioeconomic characteristics of the complete survey (General Medical Council 2013b; General Medical Council 2013a) and our sample, finding that differences between our sample and population mean values are all smaller than three percentage points (see Table 2.1). The 13,359 doctors carrying out foundation training were excluded from the analysis since they had not selected their specialty, resulting in 27,530 doctors being included in the analysis sample. These were divided into two groups for analysis, a *General sample* containing all doctors in specialty training and a *UK sample* comprised of 18,588 who received both secondary and university education in the UK. Figure 2.1 illustrates the construction process of the *General sample* and *UK sample*.

2.2.1 Independent variables

Table 2.2 sets out the variables from the NTS. For each individual there is information on their demographic and socioeconomic characteristics which we encoded as categorical or binary dummy variables: variable *Man* was assigned the value one if the doctor is a man; *BME* has the value one for black and minority ethnic doctors; age was given in four bands < 30, $30 - 39$, $40 - 49$ and $50+$ which we merged into two groups and defined the variable *Mature* to take the value one if the individual if 40 years-old or older, and variable *UK University* is equal to one if a doctor completed their medical undergraduate studies in the UK.

For the *UK sample*, there is additional information concerning parental education and socioeconomic proxies. The variable *Parent uni* takes the value one if at least one parent has tertiary education. The variables *State*, *Grammar* and *Independent* take the value one according to the type of secondary school attended. *State* school is the omitted category in the multivariate analysis. Following Milburn (2014) school type is used as a proxy for socioeconomic background. In the United Kingdom approximately 7% of pupils attend independent schools, of which only 1% receive means-tested scholarships.[5] The estimates from the *School* variable can also be informative of the degree of success of state schools in fostering their student population to enter the elite professions.

2.2.2 Dependent variables

Each doctor could be assigned to one of thirteen categories of training according to their *specialty*. We reduced this categorisation to six groups of specialties that have the same core training or that can be regarded as close substitutes (Health Careers 2017b). The resulting specialties analysed are:

- Acute care, emergency medicine and anaesthetics (ACEM)
- General Practice (GP)
- Surgical (SUR)
- Hospital based specialties including medical specialties, paediatrics and childcare, medical-surgical specializations (i.e obstetrics, gynaecology and ophthalmology) and occupational medicine (HBS)
- Psychiatry (PSY)

[5] Independent school fees in the UK are on average £15,500 per academic year (Independent 2016).

- Others including pathology, radiology and public health (OTH)

The NTS also includes the variable trust name that informs about the *Location* where doctors carry out their specialty training. We associate each trust to the corresponding LETB and group those into six categories taking into account those LETBs that are close enough and might be perceived as substitutes by doctors. The resulting locations are:

- East of England, East and West Middlands (MID)
- London (LON)
- Thames Valley and Kent Surrey and Sussex (TVKSS)
- South West Peninsula, South West Severn and Wessex (SOU)
- North East, North West Mersey, North West North Western and Yorkshire and the Humber (NOR)
- North Ireland, Scotland, Wales and Military (OTH)

For interpretation purposes, we classify *Specialty* and *Location* into *high-demand* and *low-demand* as Table 2.3 sets out. The classification is based on average competition ratios, given by the number of applications divided by the number of training posts, from the different specialties/locations for the years 2012-2015. Each year on average the number of applications submitted by doctors is double the number of training posts. Therefore, we define alternatives with historical competition ratios lower than two as *low-demand* and those with a competition ratio greater than two as *high-demand*.

2.2.3 Limitations

As with any survey there are missing data and our study is further limited by confidentiality requirements that reduced the sample we were able to analyse. Since covariates with missing observations only account for 0.5% and 5.7% of our *General sample* and *UK sample* respectively, we proceeded as if data were missing completely at random (MCAR) and based our analysis on a sample of complete observations. Comparing our sample to the full survey population did not reveal any differences greater than three percentage points in the means of the variables of interest. Nevertheless, there is always a possibility that our sample is biased in ways that cannot be detected by simple comparison of means.

Although we analyse the allocation of doctors across *Specialties* and *Locations* separately, these two elements are interdependent as often doctors face trade-offs when choosing between their desired location and their desired specialty. For example, doctors may consider as alternatives training posts, i.e. the combination of specialty and location, instead of *Specialties* and *Locations* separately. Notwithstanding, the empirical analysis of the distribution of doctors across training posts entails the consideration of a large set of alternatives that will complicate the interpretation of results and will render the Mixed Logit estimation almost impracticable. Our simpler approach is still very informative in highlighting major disparities across specialties and locations. Moreover, as the thesis focuses on specialty determinants, we draw attention to the estimation of results and discussion of the findings for *Specialty* in the main body of the chapter and place the results for *Location* in the Appendix.

2.3 Econometric model and empirical implementation

The NTS 2013 is a data set on actual outcomes, this is the final allocation of an individual i to a specific specialty/location j and there is no information on other alternatives to those chosen. Those outcomes are the product of a complex allocation process that results from the combination of doctors' application outcomes and the selection outcomes that arise from selectors' preferences over the set of candidates. Despite only observing the final outcome of the process, we seek to examine whether the process operates so as to sort doctors according to their demographic or socioeconomic characteristics. In Chapter 3, we describe the functioning of the specialty allocation process in detail, we set out a conceptual framework and an empirical approach that acknowledges the two-sided nature of the process with the goal of disentangling whether doctors' socioeconomic characteristics affect application and selection decisions differently.

We observe a dichotomous variable Y_{ij} that takes value one if we observe a doctor, i, training in specialty j and zero otherwise as shown by expression (2.1). The same relationship holds between doctors and locations.

$$Y_{ij} = \begin{cases} 1\,if \quad Y_i = j \\ 0\,if \quad Y_i \neq j \end{cases} \tag{2.1}$$

We define Y_{ij} to depend on the socio-demographic characteristics of the doctors represented by the vector Z_{ij} and that include the variables *Man*, *BME*, *Mature* and *UK University* for the *General sample* and for the *UK sample* it also includes *School* and *Parent Uni*. Ideally, we would include two other sets of covariates: one representing the value of the individual to the specialty, e.g. specific investments made by individuals, measures of ability, etc. and the other representing the attributes of the specialty in relation to the individual, e.g. distance from the training hospital to doctor's residence, expected earnings, etc. However, this is not possible as the NTS does not contain any of the information required to identify these covariates and therefore we need to assume that the omitted variables are orthogonal to the vector Z_{ij} and that our estimates do not suffer from omitted variable bias. We considered the inclusion of alternative specific information that is freely available, such as the length of training or the estimated income from the different specialties, however we do not include those as they are constant for all doctors in the sample and therefore we are not able to identify their effects individually in the estimation process.

$$Y_{ij} = \gamma_{0j} + Z_{ij}\gamma_j + \mu_{ij} \tag{2.2}$$

Expression (2.2) shows the relationship between the outcome variable and doctors' socio-demographic characteristics, where μ_{ij} represents the error term. Since specialties/locations are defined as mutually exclusive categories a Multinomial Logit approach (McFadden 1974) gives a natural means of establishing the effect of doctors' characteristics on the probability of observing them in one specialty/location, conditional on fixing their other characteristics. Each specialty/location is treated as an alternative and we compute the probability P_{ij} of an individual i to be in specialty/location j as given by expression (2.3).

$$P_{ij} = Pr(Y_i = j|z_i) = F_j(z_i\gamma_1, , z_i\gamma_m) = \frac{e^{z_i\gamma_j}}{\sum_{l=1}^{m} e^{z_i\gamma_l}} \tag{2.3}$$

The Multinomial Logit ensures that $0 < P_{ij} < 1$ and that

$$\sum_{j=1}^{m} P_{ij} = 1$$

The alternatives are mutually exclusive, exhaustive and represent a finite set. A normalization of parameters is needed as a consequence of the restriction that probabilities sum to one. The coefficients of one of the alternatives are normalised to zero, and the interpretation of the results are relative to the reference category.

The Multinomial Logit Model assumes the error term to be *iid* type II extreme value[6] distributed and also implies proportional substitution across alternatives, i.e. the assumption of Independence of Irrelevant Alternatives (IIA), given the analyst's specification. This is a very restrictive assumption that can be easily violated if the alternatives are perceived to be substitutes or if some variables in common to two or more alternatives are omitted. Violating the IIA will lead to inconsistent estimations. In order to eliminate the risk of violating the IIA we implement an alternative approach that does not require the IIA. Following Hole (2007), we fit our the Multinomial Logit model with unobserved heterogeneity to the Mixed Logit Model (McFadden and Train 2000), also known as Random-Parameters Logit. We capture the heterogeneity by allowing the constant term in the model to vary across individuals following a normal distribution, $\gamma_{0ji} = \gamma_{0j} + v_{ji}$ where $v_{ji} \sim \mathcal{N}(0, \Sigma)$ and allowing the random estimates from the different alternatives to be correlated. This relaxation of the IIA comes at the expense of a more computational cumbersome procedure, especially as we increase the number of alternatives and covariates.

Empirical implementation

In the regression tables we report the maximum likelihood coefficient estimates (MLE), their associated z-scores and the implied odds ratios (OR). Odds ratios permit an easy interpretation of the effect of dummy variables in the probability of observing the outcome variable. The odds ratio is defined as the ratio of probabilities and given by the expression (2.4) where if $e^{\gamma_k} > 1$ then having $Z_k = 1$ augments the probability of

[6] When assuming that the errors μ_{ij} are *iid* type II extreme value, the density function will be: $f(\mu_{ij}) = exp^{-\mu_{ij}} exp(-exp^{\mu_{ij}})$. An important property of this distribution is that the difference of two alternatives, e.g. $\mu_{ij} - \mu_{ik} when j \neq k$, follows a multinomial distribution.

observing $Y_i = j$ whilst when $e^{\gamma_k} < 1$ then having $Z_k = 1$ decreases the probability of observing $Y_i = j$.

$$\frac{\left[\dfrac{P_j}{1-P_j}\right]_{Z_k=1}}{\left[\dfrac{P_j}{1-P_j}\right]_{Z_k=0}} = e^{\gamma_k} \tag{2.4}$$

We set general practice, GP, as the omitted category; it is the single largest category and recurrent problems in recruitment to general practice make it a relevant object of comparison. For location, the MID is the omitted category as it is located in the centre of the UK and, after London, comprises the largest number of doctors in training.

2.4 Results

2.4.1 Descriptive statistics

Tables 2.4 and 2.5 show the distributions of individuals' characteristics by specialty for the *General sample* (N=27,516) and the *UK sample* (N=18,588), respectively. If the allocation process is unaffected by doctors' demographic and socioeconomic characteristics we would expect a similar distribution of characteristics in every specialty. In the latter case each specialty would appear as a random sample from the overall population of doctors in training. The descriptive statistics show a different picture.

The results for the *General sample* show that 45.49% of the total sample consists of *Men*, however their distribution across specialties is highly unequal as in SUR men make up 78.38% of the total whilst in GP they constitute only 30.72%. The specialties ACEM and OTH also show an over-representation of male doctors. In terms of ethnicity, the greatest deviations from the overall percentage of *BME* (41.05%) are observed for ACEM (22.85%) and for PSY (56.21%). The overall percentage of *Mature* doctors in the *General sample* is 5.1%, the lowest value being found for ACEM (2.02%) and the largest in PSY (17.14%). Similar differences emerge for the variable *UK university*. The percentage of *Overseas* students is equal to 29.44%, however their distribution across specialties is highly unequal, the largest representation being observed in PSY (54.19%) and the smallest in ACEM (18.25%) and SUR (24.7%), respectively.

Table 2.5, concerns the *UK sample* that includes the additional socioeconomic variables. In this group the percentage of *Men* (41.6%) is smaller than in the *General sample*, however their distribution across specialties remains unequal as only 26.66% of *Men* are in GP whilst 75.86% are training in SUR. The percentage of *BME* doctors is substantially smaller (25.27%) and their distribution across specialties is more balanced. The largest representation can be found in OTH (31.16%) and the smallest in ACEM (12.53%). Similarly, the percentage of *Mature* doctors is smaller (1.35%), the largest disparities being found for ACEM (0.3%) and PSY (5.42%) as in the *General sample*.

The *UK sample* also includes information on socioeconomic variables. Overall, doctors have attended an *Independent* school in a larger proportion (35.31%) than the general UK population (approximately 7%). There is again an uneven distribution across specialties; SUR being the group with the largest representation (42.19%) and GP the smallest (29.93%). We observe the opposite for *State* school with the largest representation of doctors in GP (44.57%) and the smallest in SUR (32.43%). The other socioeconomic variable present in the data is *Parent uni*, the percentage of doctors with at least one parent with tertiary education being equal to 65.83%. There is relatively little variability across specialties, the smallest value being found for GP (65.83%) and the largest for HBS (68.7%).

2.4.2 Regression results

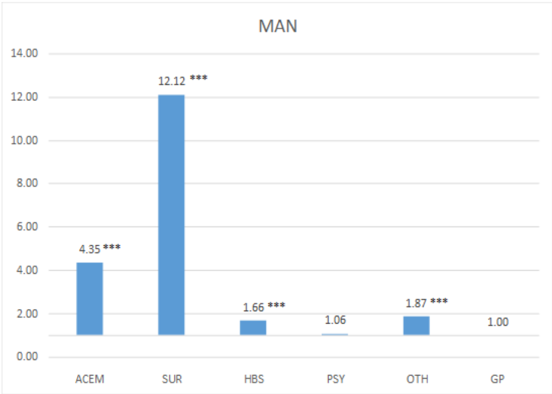
2.4.2.1 Estimation results: *General sample*

Table 2.6 and Figure 2.2 show the results for the *General sample*. In terms of gender, we observe a positive effect of the variable *Man* for all of the specialties relative to GP, confirming the relationships observed in the descriptive statistics. The greatest effects are associated with SUR and ACEM where male doctors are 12.12 and 4.35 times more likely to be allocated relative to the GP. Both effects are statistically significant at the 99% confidence level. No significant effects are found for PSY. The variable *BME* shows negative estimates for all the categories with respect to the base outcome. In this case, the largest effect is found in the ACEM category, with an odds ratio of 0.29, implying that an ethnic minority doctor is approximately 70% less likely to be based in ACEM with respect to GP. The estimates for SUR and HBS are also statistically significant and the odds ratios are 0.76 and 0.88, respectively. The regression estimates for the variable *Mature* coincide with the results observed in the descriptive statistics. The greatest positive effect, statistically significant at the 99% confidence level, was found for PSY with an odds ratio of 2.92. The rest of the categories show negative coefficients and odds ratios smaller than one, implying that being 40 or older reduces the probability of being based in any of these specialties relative to GP. The largest negative effect is found for OTH and equal to 0.27. Finally, the estimates for the variable *UK University* show a positive and significant effect for SUR, such that a UK-educated doctor is 2.07 times more likely to be training in that specialty with respect to GP. The results for ACEM are also positive and statistically significant. The greatest negative effects, statistically significant at the 99% confidence level, are found for PSY and OTH where the odds ratios associated are 0.21 and 0.52, implying that overseas graduated doctors are approximately 70% and 50% more likely to be training for PSY and OTH, with respect to GP.

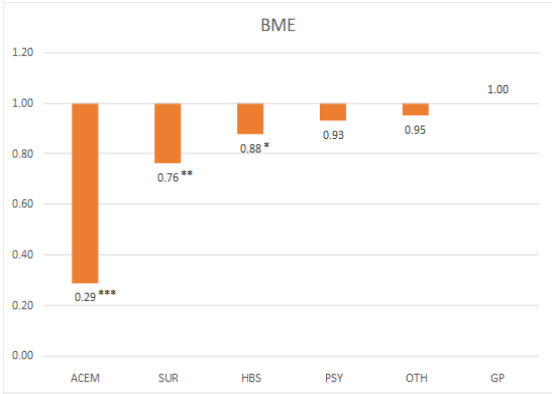
2.4.2.2 Estimation results: *UK sample*

Table 2.7 and Figure 2.3 show the results for the *UK sample*, those doctors who completed both secondary school and undergraduate studies in the United Kingdom. The estimated coefficients and odds ratios for the variables *Man*, *BME* and *Mature* are of the same sign and similar but slightly smaller magnitude to those shown in Table 2.6. With respect to schooling variables (*State* school is omitted category), which we use to proxy socioeconomic background, we observe positive and significant estimates and odds ratios greater than one for all specialties with respect to GP. The largest effects are found for SUR and OTH where doctors who attended an *Independent* school are 1.79 and 1.57 times more likely to be training for those specialties than those who attended a *State* school relative to GP. The smallest positive effect is associated with PSY with an associated odds ratio of 1.30. All the estimates are statistically significant at the 99% confidence level. Overall, having attended an *Independent* or *Grammar* school reduces the probability of being in training for general practice with respect to any other specialty. The estimates for *Parent uni* are positive, however modest compared to the schooling estimates. The greatest effect in magnitude is related to HBS and PSY with associated odds ratios of 1.31 and 1.32 respectively, both are

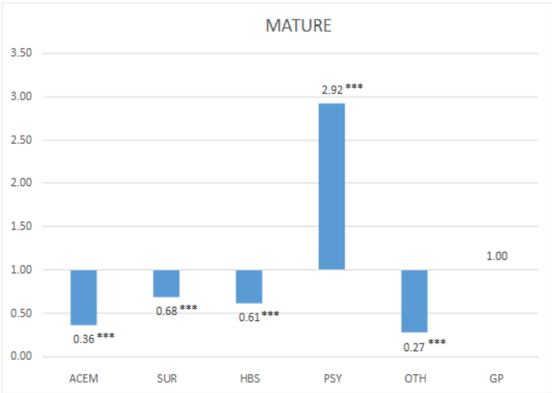
Figure 2.2: Estimated Odds Ratios for the *General Sample*



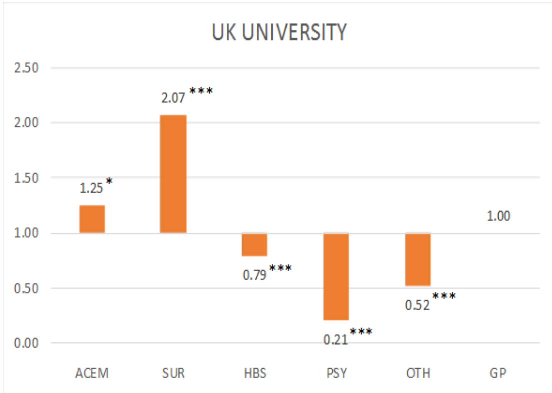
(a) Variable Men



(b) Variable BME



(c) Variable Mature



(d) Variable UK University

ACEM: acute care, emergency medicine and anaesthetics; SUR: surgical specializations; HBS: hospital based specialities; PSY: psychiatric specialties; OTH: pathology, radiology and public health; GP: general practice (omitted category)

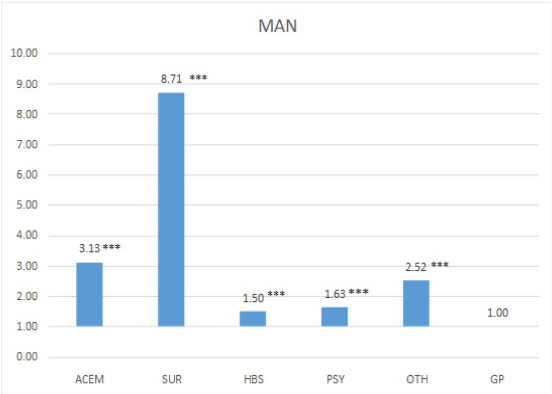
$* * *p < 0.01; * * p < 0.05$ and $*p < 0.1$

statistically significant at the 99% confidence level.

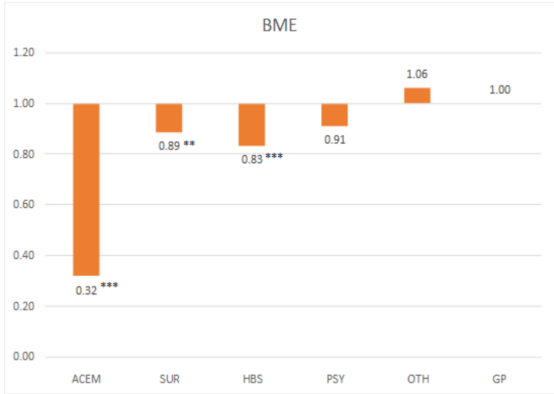
2.5 Discussion

Our analysis shows that with respect to doctors' socio-demographic characteristics there are substantial differences across specialties. Doctors training in the most demanded specialties, i.e. specialties with the greater competition ratios, are more likely to be male, white, younger, have attended an independent or grammar school, have a parent with tertiary education, and have attended a UK university. By contrast, doctors training in general practice and psychiatry, the two least demanded specialties, are more likely to be from an ethnic minority and to be older. Moreover, being a female doctor increases the probability of being in general practice, and having graduated

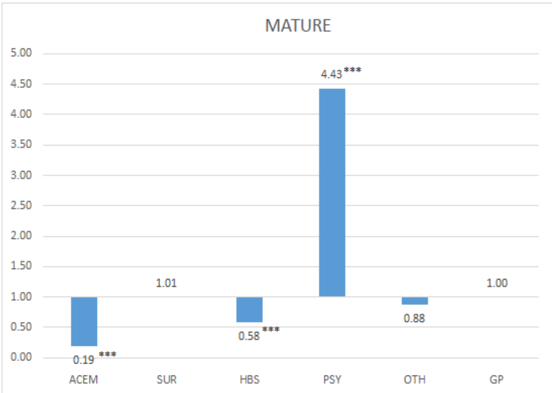
Figure 2.3: Estimated Odds Ratios for the *UK Sample*



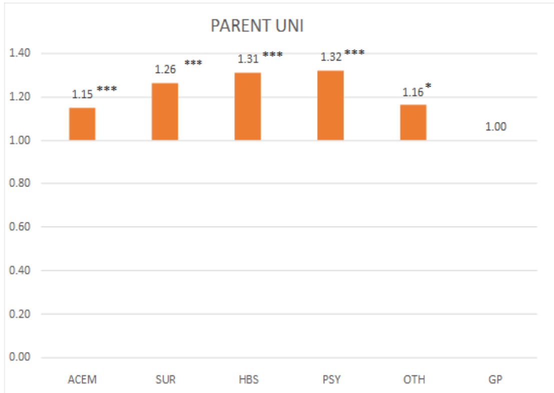
(a) Variable Men



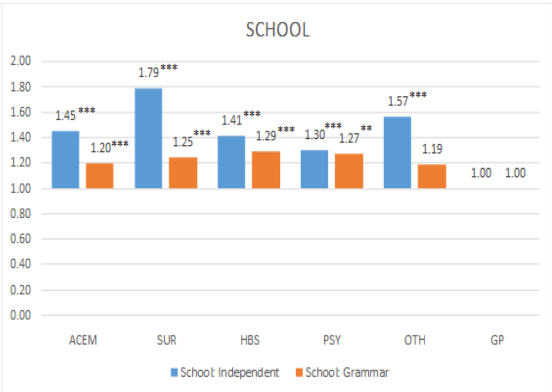
(b) Variable BME



(c) Variable Mature



(d) Variable Parent Uni



(e) Variable School

ACEM: acute care, emergency medicine and anaesthetics; SUR: surgical specializations; HBS: hospital based specialities; PSY: psychiatric specialties; OTH: pathology, radiology and public health; GP: general practice (omitted category)

$***p < 0.01; **p < 0.05$ and $*p < 0.1$

from an overseas university increases the probability of training in psychiatry.

There are many attributes that are different between *high-demand* and *low-demand* specialties, one of the most evident being the differences in income.[7] The differences are not only associated with NHS income, but also to private income where primary care specialties such as general practice have associated the lowest income estimates and surgical specialties the highest (Morris et al. 2008). Despite the feminization of the medical workforce, their unequal distribution across specialties makes female doctors more likely to be training in *low-demand* specialties, a situation that will feed into the perpetuation of the gender wage gap in the medical profession.

We find that doctors from better-off socioeconomic backgrounds are more likely to be training in a *high-demand* specialty than those who come from less privileged backgrounds. This result could be due to doctors' different application behaviour, as doctors from privileged backgrounds might have different valuations of the monetary and non-monetary attributes associated with *high-demand* specialties. Alternatively, the underrepresentation of doctors from deprived backgrounds in *high-demand* specialties might be driven by the selectors side. It is quite likely that higher skills[8] investments are needed to guarantee access to *high-demand* specialties as they present higher competition ratios and the opportunity costs associated with those investments are most likely lower for doctors who come from better-off backgrounds. This situation is likely to perpetuate inequities in the distribution of wealth among socioeconomic groups and it is especially concerning as specialty training is funded with general taxation. Policy interventions should, therefore, aim to subsidise the acquisition of the skills required to access *high-demand* specialties for those individuals from worse-off backgrounds.

Our results highlight another potential cause for concern. Approximately 30% of doctors in the training scheme are graduates from an overseas medical school and they are very unequally distributed, being largely overrepresented in *low-demand* specialties. From an international perspective importing doctors from low-income countries might be seen as brain drain and in conflict with what has been termed *Ethical Recruitment* (Lowell and Findlay 2001). Additionally, Richards (1994) and Welsh (2000) suggest that the allocation of overseas educated doctors to less desirable

[7] Morris et al. (2008) provide estimates the mean NHS and private incomes associated with each specialty.

[8] The required skills vary from specialty to specialty, but in general the skills can be obtained through extracurricular training courses or through extracurricular unpaid clinical training.

training positions might be creating an *underclass* within the NHS. This is a concern for both policymakers and the profession. Future research might usefully focus on the quality of the training experience and satisfaction of those overseas doctors and on whether a possible worse training satisfaction can influence patient outcomes.

Our results describe the outcome of a complex process of specialty allocation in which doctors apply, are selected, and subsequently choose from the offers that are made to them. We have established that the outcome of this process is highly unbalanced and that some specialties exhibit a dearth of doctors with some characteristics, and we have highlighted some of the many potential causes for such an imbalance. Alternatively, we conjecture that another determinant of the observed differences between sociodemographic groups in their sorting across specialties might be due to the existence of some form of statistical discrimination phenomena. Fang and Moro (2010) describe the latter as a theory of inequality between groups that is based on stereotypes that do not arise from prejudice or racial and gender bias. The phenomenon can affect both sides of the specialty allocation process: the selectors and the applicants (doctors). Regarding the former, Phelps (1972) establishes that the differential treatment comes from a setting where decision-makers have imperfect information about individuals, and group identity serves as a proxy for unobserved variables. Differential treatment will be observed if groups are believed to have a different distribution of skills at population level, or even if the unconditional distribution of skills is the same, the groups present a different variance of the error term of the information signal that decision-makers receive. The differential treatment can be aggravated with selectors' risk aversion, as in Aigner and Cain (1977) model. As an example, given two doctors with identical distribution of skills but one belonging to the UK graduate sample and the other to the overseas graduate sample, if we assume the latter type of doctor to have a higher variance in her information sign, due to language difficulties or cultural differences as in Lang (1986), she will be perceived as a *riskier* choice by selectors with respect to the UK candidate. The differential treatment described above might also exist between white and ethnic minority doctors, or between doctors from privileged and deprived socioeconomic backgrounds.

Regarding doctors' behaviour, Arrow (1973) proposes a model where the differences in outcomes between groups that are identical ex-ante, are derived in equilibrium and are based on a *self-fulfilling prophecy*. In the UK specialty allocation context, the latter means that if for some reason one of the groups, e.g. female doctors or doctors from deprived socioeconomic backgrounds, believes that their chances of obtaining the *high-demand* training posts are smaller than the dominant group, i.e. male or privileged doctors, the minority group would have less incentives to invest in the necessary skills to obtain those training posts, being skill acquisition endogenous in Arrow's model. The minority group will invest less and they will be believed to be qualified with lower probability. Fang and Moro (2010) claim that Arrow's insight depends on unobserved human capital investments and that it is worth testing whether returns to observable human capital investments, such as education, should be different or higher for the dominant group. One of the proposed measures to tackle the *self-fulfilling prophecy* is the introduction of affirmative-action policies that will maximise doctors' quality for any level of diversity as Chan and Eyster (2003) do for student admission to college. By contrast, Coate and Loury (1993) found mixed results for the implementation of affirmative action and suggest that those might lead to a *patronising equilibria* where the standards for the minority group are lowered, whilst the standards for the majority group must be raised, therefore lowering the incentives for skill investment in the minority group. Future research could focus on the evaluation of the suitability of affirmative action policies to tackle the disparities across specialties.

The statistical discrimination literature also tries to explain occupational gender segregation. Altonji and Blank (1999) link the fact that women are more likely to work part-time to their lower presence in technical occupations, as those occupations exhibit higher depreciation rates. In the medical context, the fact that depreciation rates and technical change are larger for surgical specialties than for primary care specialties might lead female doctors to be disproportionately attracted to the second group. Johnson and Stafford (1995) suggest that the consequences of institutional constraints, social norms, or employer discrimination might *crowd* a group into particular occupations. Finally, Manski (1993a) highlights the informational value of close role models in the decision-making process. In the medical context, according to Fitzgerald et al. (2013) the lack of female role models it has been considered a detractor in recruiting more women to the field of surgery. Chapter 4 analyses the impact of informational role models in doctors' specialty choices.

In contrast to previous work in this area, we have been able to examine imbalances in both demographic and socioeconomic characteristics simultaneously using a survey that contains rich information on individuals and has a very high response rate. Our results are therefore both novel and more comprehensive than previously it has been possible to generate. However they are necessarily specific to the particular sample of doctors studied. A limitation is that there are characteristics of individuals that are relevant to understanding their specialty allocation that are not reported in this survey. In particular, the educational background of doctors in training, with respect to the medical school they attended and their academic records, could potentially be confounders of the estimates of demographic and socioeconomic characteristics. The analysis in Chapter 3 addresses this limitation.

Identifying the causes of the imbalances we have documented has considerable importance for policymakers who are concerned to redress them. Medical education is costly and in the UK relies upon a substantial injection of public funds. It is therefore natural that policymakers will be concerned that the outcome of medical education reflects societal values, and a key task for future research is to find the means of discriminating between competing explanations for the reflection it does provide. Therein lies the means to intervene successfully. In the remainder of this thesis we explore some of the competing explanations.

Acknowledgements

We gratefully acknowledge the General Medical Council for providing the data used in this chapter.

2.6 Tables

Table 2.1: Descriptive statistics of the NTS population vs. Our sample

	All NTS Respondents[a]	Our Sample (incl. foundation trainees)	General Sample
	N=52,797	N=40,889	N=27,530
Man	45.00%	43.76%	45.50%
% of Foundation trainees	27.70%	32.70%	
Socioeconomic Variables			
	N=38,933	N=31,138	N=19,425
Parent uni	65.00%	66.01%	68.10%
School: State	38.80%	38.93%	39.90%
School: Independent	33.70%	33.82%	36.60%
School: Grammar	23.70%	24.06%	23.50%
Income Support	11.50%	11.34%	11.30%

[a] Descriptive statistics for the NTS 2013 population can be found in the GMC webpage (General Medical Council 2013b; General Medical Council 2013a)

Table 2.2: Variables in the National Training Survey

Independent Variables	
Man	1 if the individual is a male, 0 otherwise.
BME	1 if the individual is Black and minority ethnic, 0 otherwise.
Mature	1 if the individual is 40 years-old or older, 0 otherwise.
UK university	1 if the individual attended both secondary school and medical studies in the UK, 0 otherwise.
Only for the *UK sample*	
School: State	1 if the individual attended a state non selective school, 0 otherwise.
School: Grammar	1 if the individual attended a state selective school, 0 otherwise.
School: Independent	1 if the individual attended a fee paying/independent school, 0 otherwise.
Parent uni	1 if any of the individual's parent(s) or guardian(s) completed a University degree course of equivalent, 0 otherwise
Dependent Variables	
Specialty	Categorical variable indicating the specialty the individual is training for. Six Categories see Section 2.2.2.
Location	Categorical variable indicating the region where the individual is undertaking the specialty training. Six Categories see Section 2.2.2.

Table 2.3: Classification of *specialties* and *locations* into low and high-demand according to 2012-15 competition ratios

	Low-Demand	**High-Demand**
Specialty		
ACEM		x
HBS		x
GP	x	
SUR		x
PSY	x	
OTH		x
Location		
MID	x	
LON		x
TVKSS		x
SOU	x*	
NOR	x*	
OTH		x

[a] Source: NHS Health Education England

[b] The classification is based on average competition ratios, given by the number of applications divided by the number of training posts. Each year on average the number of applications submitted by doctors is double the number of training posts. We define alternatives with historical competition ratios lower than two as *low-demand* and those with a competition ratio greater than two as *high-demand*.

[c] ACEM: acute care, emergency medicine and anaesthetics; GP: general practice; SUR: surgical specializations; HBS: hospital based specialities; PSY: psychiatric specialties; OTH: pathology, radiology and public health.

[d] MID: East of England, East and West Midlands; LON: London; TVKSS: Thames Valley and Kent Surrey and Sussex; SOU: South West Peninsula, South West Severn and Wessex; NOR:North East, North West Mersey, North West North Western and Yorkshire and the Humber; OTH: North Ireland, Scotland, Wales and Military.

[e] * With the exception of Severn; ** With the exception of Mersey

Table 2.4: Characteristics of the doctors in the *General sample*

	ALL		**ACEM**		**GP**		**SUR**		**HBS**		**PSY**		**OTH**	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Gender														
Man	12,524	45.49	1761	53.22	2,134	30.72	3,104	78.38	4,030	40.2	914	42.81	581	50.26
Woman	15,006	54.51	1548	46.78	4,812	69.28	856	21.62	5,994	59.8	1,221	57.19	575	49.74
Ethnicity														
BME	11,301	41.05	756	22.85	2,890	41.61	1,628	41.11	4,322	43.12	1,200	56.21	505	43.69
White	16,215	58.9	2553	77.15	4,056	58.39	2,328	58.79	5,692	56.78	935	43.79	651	56.31
Missing	14	0.05					4	0.1	10	0.1				
Age														
40 years old or more	1,404	5.1	67	2.02	344	4.95	184	4.65	426	4.25	366	17.14	17	1.47
Less than 40 years old	26,126	94.9	3,242	97.98	6,602	95.05	3,776	95.35	9598	95.75	1,769	82.86	1,139	98.53
Place of studies														
UK	19,425	70.56	2,705	81.75	5,226	75.24	2,982	75.3	6,767	67.51	978	45.81	767	66.35
Overseas	8,105	29.44	604	18.25	1,720	24.76	978	24.7	3,257	32.49	1,157	54.19	389	33.65

[a] ACEM: acute care, emergency medicine and anaesthetics; GP: general practice; SUR: surgical specializations; HBS: hospital based specialities; PSY: psychiatric specialties; OTH: pathology, radiology and public health.
[b] BME: Black and minority ethnic

Table 2.5: Characteristics of the doctors in the *UK sample*

	ALL		**ACEM**		**GP**		**SUR**		**HBS**		**PSY**		**OTH**	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Gender														
Man	8,081	41.6	1,369	50.61	1,393	26.66	2,262	75.86	2,334	34.49	361	36.91	362	47.2
Woman	11,344	58.4	1,336	49.39	3,833	73.34	720	24.14	4,433	65.51	617	63.09	405	52.8
Ethnicity														
BME	4,909	25.27	339	12.53	1,432	27.4	926	31.05	1,709	25.25	264	26.99	239	31.16
White	14,504	74.67	2,366	87.47	3,794	72.6	2,052	68.81	5,050	74.63	714	73.01	528	68.84
Missing	12	0.06					4	0.13	8	0.12				
Age														
40 years old or older	261	1.34	8	0.3	71	1.36	56	1.88	63	0.93	53	5.42	10	1.3
Less than 40 years old	19,164	98.66	2,697	99.7	5,155	98.64	2,926	98.12	6,704	99.07	925	94.58	757	98.7
School type														
State	7,490	38.56	1,030	38.08	2,329	44.57	967	32.43	2,522	37.27	370	37.83	272	35.46
Grammar	4,414	22.72	610	22.55	1,166	22.31	610	20.46	1,627	24.04	236	24.13	165	21.5
Independent	6,859	35.31	962	35.56	,564	29.93	1,258	42.19	2,430	35.91	340	34.76	305	39.77
Missing	662	3.41	103	3.81	167	3.19	147	4.93	188	2.78	32	3.27	25	3.26
Parental University														
Yes	12,788	65.83	1,747	64.58	3,237	61.94	1,978	66.33	4,649	68.7	669	68.4	508	66.23
No	6,000	30.89	855	31.61	1,827	34.96	859	28.81	1,943	28.71	282	28.83	234	30.51
Missing	637	3.28	103	3.8	162	3.1	145	4.87	175	2.49	27	2.76	25	3.26
Income Support														
Yes	1,988	10.23	282	10.43	581	11.12	297	9.96	627	9.27	101	10.33	100	13.04
No	15,609	80.36	2,157	79.74	4,146	79.33	2,377	79.71	5,541	81.88	795	81.29	593	77.31
Missing	1,828	9.41	266	9.83	499	9.55	308	10.33	599	8.85	82	8.38	74	9.65

[a] ACEM: acute care, emergency medicine and anaesthetics; GP: general practice; SUR: surgical specializations; HBS: hospital based specialities; PSY: psychiatric specialties; OTH: pathology, radiology and public health.
[b] BME: Black and minority ethnic

Table 2.6: Mixed Logit regression estimates for the *General sample*

	ACEM		**SUR**		**HBS**		**PSY**		**OTH**	
Man	1.471	4.354	2.495	12.121	0.507	1.660	0.061	1.063	0.626	1.869
	(5.63)***		(15.2)***		(4.43)***		(-0.68)		(6.18)***	
BME	-1.240	0.289	-0.271	0.763	-0.131	0.878	-0.071	0.932	-0.050	0.951
	(-9.18)***		(-2.44)**		(-1.73)*		(-0.86)		(-0.56)	
Mature	-1.021	0.360	-0.380	0.684	-0.496	0.609	1.071	2.918	-1.309	0.270
	(-4.97)***		(-2.58)***		(-3.89)***		(5.23)***		(-4.18)***	
UK University	0.221	1.247	0.728	2.072	-0.235	0.790	-1.567	0.209	-0.655	0.520
	(1.67)*		(7.02)***		(-2.87)***		(-7.31)***		(-2.98)***	
Constant	-1.684	0.186	-2.600	0.074	0.446	1.562	-1.384	0.251	-2.962	0.052
	(-4.66)***		(-12.14)***		(5.03)***		(-3.26)***		(-6.83)***	
N	27,516									
Log-likelihood	-41153.377									

[a] ACEM: acute care, emergency medicine and anaesthetics; SUR: surgical specializations; HBS: hospital based specialities; PSY: psychiatric specialties; OTH: pathology, radiology and public health.

[b] MLE (mixlogit estimate); OR (odd ratio);

[c] Man vs. woman; BME vs. non-BME (BME: Black and minority ethnic); Mature vs. non-mature (>40 vs. <40 years old); UK university vs. overseas educated student.

[d] Z-scores in parentheses: $***p < 0.01$; $**p < 0.05$ and $*p < 0.1$;

Table 2.7: Mixed Logit regression estimates for the *UK sample*

	ACEM		**SUR**		**HBS**		**PSY**		**OTH**	
	MLE	OR	MLE	OR	MLE	OR	MLE	OR	MLE	OR
Man	1.140	3.127	2.165	8.714	0.405	1.499	0.491	1.634	0.924	2.520
	(21.73)***		(34.57)***		(6.78)***		(5.94)***		(10.43)***	
BME	-1.145	0.318	-0.120	0.887	-0.181	0.834	-0.092	0.912	0.061	1.063
	(-16.27)***		(-2.1)**		(-3.9)***		(-1.08)		(0.68)	
Mature	-1.648	0.193	0.005	1.005	-0.545	0.580	1.488	4.428	-0.133	0.876
	(-4.35)***		(0.03)		(-2.75)***		(6.75)***		(-0.38)	
Parent Uni	0.139	1.149	0.235	1.265	0.271	1.311	0.278	1.321	0.149	1.161
	(2.6)***		(4.23)***		(6.1)***		(3.38)***		(1.69)*	
Independent School	0.373	1.452	0.582	1.789	0.346	1.413	0.263	1.301	0.448	1.566
	(6.42)***		(9.75)***		(7.14)***		(2.99)***		(4.76)***	
Grammar School	0.179	1.196	0.221	1.247	0.254	1.289	0.241	1.272	0.170	1.186
	(2.78)***		(3.27)***		(4.85)***		(2.52)**		(1.58)	
Constant	-1.141	0.320	-2.062	0.127	-0.212	0.809	-2.514	0.081	-2.824	0.059
	(-16.19)***		(-25.15)***		(-3.29)***		(-12.99)***		(-16.04)***	
N	18,588									
Log-likelihood	-27595.305									

[a] ACEM: acute care, emergency medicine and anaesthetics; SUR: surgical specializations; HBS: hospital based specialities; PSY: psychiatric specialties; OTH: pathology, radiology and public health.
[b] MLE (mixlogit estimate); OR (odd ratio); CI -OR (OR confidence interval)
[c] Man vs. woman; BME vs. non-BME (BME: Black and minority ethnic); Mature vs. non-mature (> 40 vs. < 40 years old); UK university vs. overseas educated student.
[d] Z-scores in parentheses:$***p < 0.01$; $**p < 0.05$ and $*p < 0.1$;

Chapter 3

A sequential analysis of the specialty allocation process in the UK. Empirical evidence from the UKMED database

3.1 Introduction

There is a strong interest in ensuring that the medical profession is representative of the society it serves (General Medical Council 2010). The achievement of a greater balance, in terms of gender, ethnicity and socioeconomic background, could improve patient outcomes (Tsugawa, Jena, Figueroa et al. 2017) and foster policies targeted at improving the health outcomes of deprived populations and ethnic minorities (Cohen et al. 2002). However, the results from Chapter 2 are evidence of the existence of large disparities in the distribution of doctors across specialties with respect to doctor's demographic and socioeconomic characteristics in the UK.

The research reported in this chapter seeks to understand and disentangle the origins of the differential outcomes, recognising that the allocation of individuals to specialties is a sequential process. Doctors make decisions as to which specialties to apply for and their applications are then assessed to determine their suitability. At each stage of this process there is selection, either by the doctors themselves or by the selectors reviewing their applications, that might result in specialties becoming unbalanced in terms of social, economic, gender and ethnic characteristics. Thus, our principal objective is to understand how demographic and socioeconomic characteristics impact this process; how do an individual's characteristics correspond to their decision to apply and to their subsequent assessment by selectors from the different specialties. Such an understanding is necessary for the formulation of effective strategies to ensure greater representativeness across specialties.

For that purpose, we develop a conceptual framework that acknowledges the two-sided nature of the specialty allocation process: the application and selection stages. This framework also serves as the basis of the empirical analysis we perform. First, we focus on the application stage and estimate by means of a set of Probit regressions the relationship between an individual's characteristics and their propensity to apply for training in different specialties, controlling for their educational background and attainment. Answering this question establishes whether specific groups are either discouraged from or have preference against applying for specialties. It can therefore inform policies specifically targeting doctors at the application stage, in order to ensure greater balance in the pool of applications. Moreover, we estimate how doctors' personal characteristics can influence their application strategies, i.e. whether doctors concentrate their efforts into a single application or engage in more than one. This analysis can be informative regarding individuals' perception of success and how that perception affects their specialty allocation outcomes.

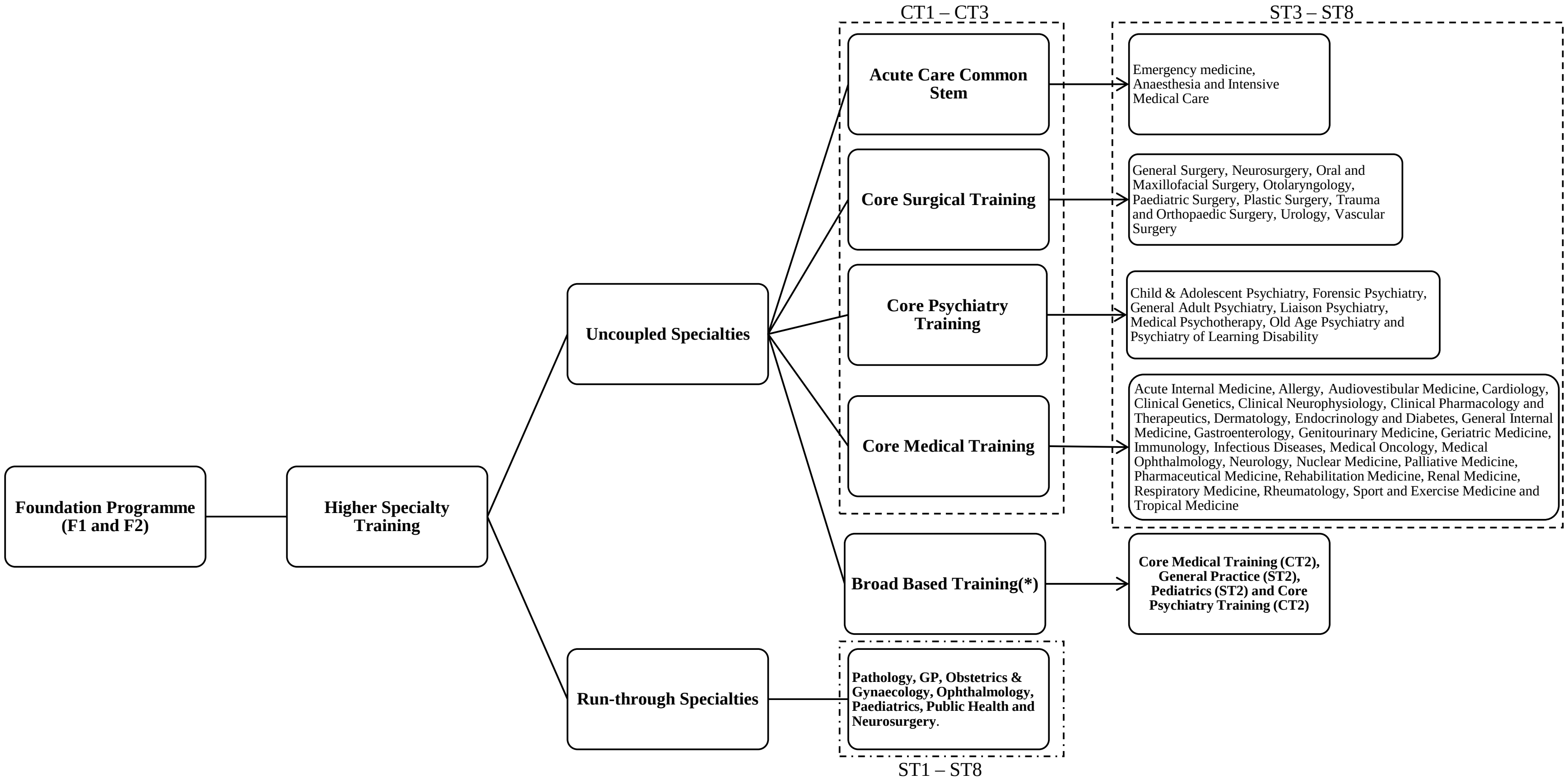
Second, we focus on the selection that takes place after doctors have made their specialty application choices. The interview is a crucial element of this selection stage. We analyse the role of demographic and socioeconomic characteristics in determining interview scores, controlling for previous educational attainment and other relevant characteristics by means of a linear regression. We also apply the Oaxaca-Blinder decomposition of the mean interview score by gender and ethnicity, with the purpose of disentangling the sources of the differences between demographic groups. Our analysis of the interview score provides evidence regarding the functioning of the selection system and whether specific groups experience differential attainment in the selection process. It will thus serve as the basis for further study of the causes of differential attainment and the identification of any necessary policy intervention.

The data used in this study come from the UK Medical Education Database (UKMED), which collates data on the performance and career progression of UK medical students and training doctors. Our data belong to the pilot phase of UKMED and include the universe of individuals who entered a UK medical school in the years 2007 and 2008. The data are unique and more comprehensive than previously available, as they link several sources of data, allowing for an empirical estimation of the sequential specialty allocation process in the UK.

The results show strong evidence with respect to selection by women, ethnic minorities and doctors from better-off socioeconomic backgrounds with regard to their application patterns. In respect of the selection stage, the results suggest the existence of unexplained interview score differences in favour of white and female doctors, with respect to ethnic minority and male doctors.

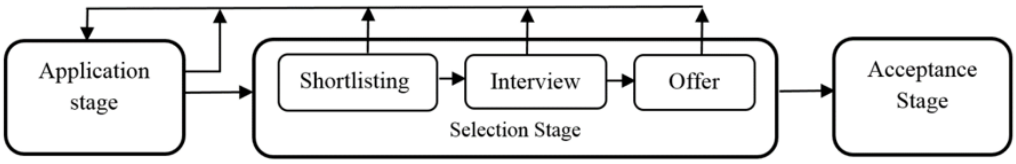
The reminder of this chapter is organised as follows: in Section 3.2 we describe in detail the functioning of the specialty allocation process in the UK. Section 3.3 sets out the conceptual framework. Sections 3.4 and 3.5 set out the background, econometric model and results from the application and selection stages, respectively. Section 3.6 concludes the chapter. Tables can be found in Section 3.7.

Figure 3.1: Specialties in the NHS



CT#: Core Training year #; ST#: Specialty Training year #.
(*) Broad Based Training is two year core training programme that give trainees six month of experience in four specialties: Core Medical Training, General Practice, Paediatrics and Psychiatry. At the end of the programme, trainees will be able to choose, without further competition, one of the four specialties to enter at CT2 or ST2.

Figure 3.2: Stages in the specialty allocation process



3.2 The functioning of the specialty allocation process in the UK

In order to establish a conceptual and empirical framework we consider the key stages of the specialty allocation process as it operates in the UK. Postgraduate training is divided in two main parts: the Foundation Programme (FP) and, the object of our analysis, the Postgraduate Specialty Training.

The FP lasts two years and is common for all medical career paths. Newly graduated doctors receive general medical training by rotating through different specialties within a university hospital. During the second year of the FP doctors need to choose a career path and prepare their applications to gain access to higher specialty training. Doctors can submit as many applications as they wish, as long as they meet the eligibility criteria. Figure 3.1 shows all the specialties available in the NHS. Specialties are divided into run-through and uncoupled, the main difference being that the latter type of training is delivered in separate core and higher specialty training programmes and requires doctors to go through the specialty allocation process twice. The length of the training also varies, it can take from a minimum of three years, to become a general practitioner, up to eight years in some specialties as, for example, in all the surgical sub-specialties (Health Careers 2017a).

The recruitment to specialty training is a two-sided process, mainly administered nationally and led by Royal Colleges or a Local Education and Training Board[9] (LETB) on behalf of all LETBs. Figure 3.2 shows the sequence of different stages that constitute the specialty allocation process.

The process starts with the application stage where the junior doctors can state their

[9]LETBs correspond to England's former deaneries.

preferences by making as many applications as they want, as long as they meet the required criteria set by each specialty. Nonetheless, the process of applying is costly in terms of time (and resources) and the Royal Colleges encourage junior doctors to take into account past information and to apply *wisely* by restricting the number of applications and by being aware of their competitiveness in relation to the rest of candidates (Royal College of Physicians 2013). The number of vacancies and past competition ratios for each specialty is public information.

Once the application period is over, the selection stage takes place. This is divided into three sub-steps: shortlisting, interview and offers. Initially, the corresponding Royal College or LETB reviews all applications and discards those that do not meet the application criteria. Then the shortlisting process starts and all applications are scored and ranked. Names and other sensitive information are concealed from selectors. Not all specialties use shortlisting, either because selection rests on an alternative assessment, as in general practice or public health, or because the interview capacity is sufficient so that all eligible applicants can be invited to the selection centre (Health Education England 2016). Top scoring candidates progress to the interview stage. Panel members have access to doctors' anonymised application forms and portfolios before the interview takes place. The interview is divided into at least two different stations and in each the candidate is independently evaluated by two interviewers. The aggregate score from all interviewers constitutes the final score. Appointments to training positions are offered in rank order, based on a combination of interview and shortlisting scores. Interviewing panels do not have access to doctors' location preferences within a specialty/core training programme. Doctors are asked to submit those preferences in the period between the application submission and the offers stage. A lower interview score translates to a lower probability of obtaining the desired training post, i.e. desired specialty and location, or in failing to be offered a position at all.

The acceptance stage finalises the process. A doctor receiving an offer has 48 hours to accept, reject or hold (until a set date) the offer. Holding an offer still allows doctors to receive upgrades[10] at any point and candidates who have accepted an offer can still

[10]Applicants can opt in for upgrades. This means that should a higher ranked preference become available and the applicant who has opted in for upgrades is next in line to receive the offer, the

apply to posts in subsequent recruitment rounds.

3.3 Conceptual framework

3.3.1 Application stage

We utilise a standard economics framework to establish the channels by which doctors' characteristics may influence their choices regarding which specialties to apply to. In this framework decisions are made to balance benefits and costs subject to various constraints.

We suppose that doctors are indexed by i and specialties by j and we define $M = \{i \in \mathbb{N} : 1 \leq i \leq N\}$ as the set that contains all doctors, $S = \{j \in \mathbb{N} : 1 \leq j \leq T\}$ as the set that contains all specialties and $Q = \{q_1, ..., q_j, ..., q_T\}$ as the capacity vector where q_j indicates the number of training posts available in specialty j.

Each doctor i associates a net benefit B_{ji} to each specialty j. The net benefit results from the difference between the gross benefit, which is a function of taste and preferences, and the cost the individual associates with the training and practice of specialty j. We assume that $B_{ji} = f(Z_i)$, where Z_i is a vector of individual characteristics. Moreover, each doctor i associates a probability of being accepted to specialty j, and this is represented by P_{ji}. The probability is subjective and reflects doctors' own perceptions and beliefs of how likely they are to be accepted to specialty j. We assume that P_{ji} is a function of the vector of individual characteristics, Z_i, and the number of training posts available, q_j. Hence we have $P_{ji} = f(Z_i, q_j)$.

According to our framework individual i will consider applying to specialty j if the net benefit, B_{ji}, is not negative. We define A_{ji} as the probability weighted net benefit individual i assigns to specialty j, $A_{ji} = P_{ji}B_{ji}$, which results from the product of the net benefit and the perceived probability associated with specialty j. Individual i ranks specialties according to their weighted net benefit A_{ji} from highest to lowest. The ranking does not necessarily coincide with the specialty order that would result from ranking specialties according to the net benefit B_{ji} solely. Therefore, the perceived probability P_{ji} has an important influence in doctors' decisions to specialize and we

applicant will be automatically upgraded to this offer with no option to revert to the original offer (Health Education England 2016).

assume it determines the number of applications a doctor makes.

In the UK doctors can make as many applications as they wish as long they meet the eligibility criteria. However, data suggest that a typical student makes one or two applications. We can interpret this as doctors having a fixed endowment of effort that can be devoted to the preparation of applications and we assume that the endowment is fixed and equal to E for all individuals. We assume that the division of the effort endowment E depends on P_{ji}. We define probability thresholds $\bar{P}_j$ for each specialty and assume those are known and equal for all individuals. The threshold is a function of the past competition ratio , c_j, associated with each specialty j, $\bar{P}_j = f(c_j)$; where c_j is defined as the number of total applications received by each specialty j, a_j, divided by its capacity, q_j. Individual i would make a unique application to the specialty with the highest A_{ji} only if $P_{ji} \geq \bar{P}_j$. If, on the contrary, $P_{ji} < \bar{P}_j$ individual i will still apply to the specialty with highest A_{ji} but also will split her effort endowment into two or more applications until for one of the options the perceived probability is larger than the correspondent threshold. The perceived probability P_{ji} does not depend on effort, is subjective and non-observed by the selectors, however the effort devoted to each application, E_{ji}, is objective and can be extrapolated from the quality of the application by selectors.

3.3.2 Selection stage

In the second stage, selectors from the different specialties, contained in the set S, decide which candidates, from the set M, are suitable to be offered a post from the set of training posts available Q. Each $j \in S$ receives a number of applications a_j which is a function of the weighted net benefit that each medical student associates with specialty j at the moment of applying, $a_j = f(A_{ji})$.

The panel of selectors of specialty j will receive a total of a_j applications. From all of those applications, only the candidates that fulfil all the admissions criteria will be assigned a shortlisting score[11] SC_{ji} that is a function of student qualifications, experience and other elements. Those candidates whose SC_{ji} is above a certain

[11] Not every specialty follows exactly the same scheme: some skip the shortlisting score step whilst some have a pre-interview assessment instead. Nonetheless, all the specialties in our sample carry out interviews and provide interview scores.

threshold $\bar{SC}_j$, set by each specialty, will be invited to be interviewed. Then, during the interview process selectors assign each candidate an interview score IS_{ji}.

The interview score, $IS_{ji} = f(SC_{ji}, Z_i, E_{ji}, u_{ji})$, is a function of doctor's qualifications that are captured by SC_{ji}, the effort exerted in preparing the application and the interview process E_{ji}, a vector of individual observable characteristics such as age, sex, medical school, etc., represented by Z_i, and a component u_{ji} that analysts do not observe and captures a set of elements that may affect the interview score, such as candidates' nervousness, communication problems, selectors' unconscious biases, etc.

Each specialty has a limited number of training posts q_j and generally $q_j < a_j$. Each doctor who has completed the selection process has a total score that is a function of shortlisting and interview scores, $TS_{ji} = f(SC_{ji}, IS_{ji})$. Selectors will rank candidates according to their TS_{ji}, from highest to lowest, and will offer training positions following this order until the capacity is met. Specialties usually set a bottom threshold for $\bar{TS}_j$ and even if there is enough capacity, candidates with a $TS_{ji} < \bar{TS}_j$ will not be offered a training position.

The relationship between the application and selection stage is made through the effort exerted by the doctors. If two doctors i and $i+1$ are both participating in the selection process of specialty j and are similar in every aspect except in the distribution of effort endowment and $E_{ji} > E_{j,i+1}$ then $TS_{ji} > TS_{j,i+1}$.

3.4 Application stage

3.4.1 Background

According to Nicholson (2008) doctors choose a specialty taking into account three domains: the monetary aspect, the non-monetary attributes and doctors' personal characteristics. The first studies addressing the determinants of specialty choice can be found for the United States and mainly focus on the estimation of the rates of return from the different specialties, like the pioneering work from Sloan (1970), and on how those rates affect specialty choice, as in Hurley (1991) or in Nicholson (2002). The latter also introduced the role of rationing and uncertainty to weigh the net present value of the returns of each specialty. Also for the US, Bazzoli (1985) analysed the impact of educational debt on specialty decisions. The cited studies provide different estimates of income elasticity of supply, close to zero in Sloan (1970) and Bazzoli (1985), to almost 1.5 in Nicholson (2002), however the latter measures the impact of income on the desired specialty, rather than the actual specialty choices which are restricted by rationing. Gagné and Léger (2005) find a positive effect of income on specialty choice for Canada and Sivey et al. (2012) for Australia.

Other studies have analysed the role of non-pecuniary aspects of the specialties. Thornton and Esposto (2003) studied the trade-off between income and leisure for the different specialties in the US, finding a positive impact on specialty selection for earnings, for more annual vacation time and for more certain work schedules. Bhattacharya (2005) included non-pecuniary aspects of the specialties in the estimation of earnings, finding that years of training, schedules, reputation and skill mix required are likely to affect life time earnings and therefore will have a significant influence in the specialty choice decision.

International literature has focused on the pecuniary aspects of specialties and the trade-off between those and non-pecuniary elements, and has viewed this trade-off as the main driver of specialty choice. For the UK, Wilson (1987) estimates the rate of return of the medical profession as a whole and compares it with the returns from other similar professions finding no significant differences. Morris et al. (2008) provide estimates for NHS and private income for consultants by specialty and region. However, there are no studies analysing how income impacts specialty choice. The monetary aspect is likely to be less important in the UK than in countries that rely on market mechanisms for services provision (e.g. US), as the NHS allows for little variation of payment between specialties. Harris et al. (2014) found for Spain, which also has a national health system, that private practice earnings, prestige and favourable lifestyle are most the important elements in the specialty choice.

The contributions to literature in the UK have focused on the role of personal characteristics in the decisions to specialise. Goldacre et al. (2004), using a postal questionnaire, asked medical graduates for their desired specialty and found significant differences between medical schools in the career choices made by their graduates. The most significant were found for the Oxbridge graduates who were less likely than other doctors to choose general practice as a career, whilst Birmingham and Leicester graduates showed the reverse. Lambert et al. (2006) compared the specialty choice of the graduates over time by means of descriptive statistics. They found that some specialties like general practice, obstetrics or gynaecology permanently attract women whilst others like surgery attract men. In addition, the authors found that the gender gap in general practice is further widening with the new cohort of doctors. Fazel and Ebmeier (2009) analysed the number of applications per vacancies for ten different specialties, finding that surgery and radiology were the most desirable specialties whilst paediatrics and psychiatry were the least for the UK graduates. Goldacre et al. (2010) compared the eventual career destinations with early specialty choices, finding a large mismatch. The differences were especially large for general practice, meaning that only a small percentage of doctors had it as first choice at an early stage in their career. Failure to get a post and disillusion with the specialty originally chosen were listed as the main drivers of the mismatches. Soethout et al. (2004) present a literature review of European studies analysing factors associated with specialty choice, finding that personal characteristics, such as enthusiasm, self-appraisal of skills or human interest, and domestic circumstances were the two main drivers.

All the cited studies analyse the effect of personal characteristics in isolation and do not account for correlation between the different elements. Moreover, their results come from surveys that, despite having good response rates, might not be fully representative of the medical workforce. In this section of Chapter 3, we focus on estimating the role of personal characteristics in UK doctors' application patterns. This is the first study to comprehensively look at the doctors' application choices in the context of the multi-stage allocation process. Our analysis is more exhaustive than has been previously possible as it is the first to consider comprehensive administrative data and to apply multivariate econometric methods that allow the estimation of the relationship between socio-demographic characteristics and decisions to specialise controlling for doctors' academic backgrounds and previous educational attainment.

3.4.2 Data and variables

The cross-sectional data used in this study come from the UK Medical Education Database (UKMED), which collates data on the performance and career progression of UK medical students and training doctors. Our data belong to the pilot phase of UKMED and include all individuals who entered a UK medical school in the years 2007 and 2008 and participated in the specialty allocation process in the period between 2012 and 2015.

3.4.2.1 Independent variables

Table 3.1 describes all the variables included in the analysis. The dataset includes information on demographic characteristics such as gender, ethnicity and age represented by the variables *Woman*, *BME* and *Age Process*, respectively. We also control for the variable *Time Elapsed* that measures the number of years in between medical qualification and the specialty allocation process.

We include measures of socioeconomic background such as *POLAR3*, that stands for Participation Of Local Areas and is an indicator of neighbourhood deprivation and classifies neighbourhoods in three groups: low-participation, non-UK and other neighbourhood, the latter includes all UK non-deprived areas. The classification groups areas across the UK and it is based on the proportion of the young population that participates in higher education. Secondary school attended, variable *School* is another measure of socioeconomic background as we consider those having attended an independent school as a proxy for coming from a high-income family (Milburn 2014). As it is well known that medical students come frequently from families with medical practitioners (Sutton et al. 2014), we include a dummy variable, *Parent Doctor*, which identifies individuals for whom at least one parent is also a medical doctor.

The objective is to estimate how belonging to a family of doctors affects individuals' application behaviour.

UKMED includes a set of academic covariates such as the results from the UK Clinical Aptitude Tests (UKCAT), variable *UKCAT Score*, that is an admission test used by UK universities. UKCAT does not contain any curriculum or science content and tests students' mental abilities, attitudes and professional behaviours. Moreover, UKCAT results constitute a reasonable proxy for A-level results (James et al. 2010). The variable *Graduate* indicates whether a doctor had already graduated from a different degree at the point of entrance to medical school. We further control for place of medical qualification, variable *Medical School*, and the *Foundation School* where the doctor did the foundation training. There are 30 medical schools and 28 foundation schools and for both, we set Birmingham as the base outcome. Birmingham has been situated in the central position of medical school rankings for the years 2013-2015 (The Guardian 2017) and therefore constitutes a good representation of an average medical school. We use the same medical school ranking to construct the dummy variable *Top 5 Uni* that takes the value one for the medical schools that have been ranked in the first five positions[12] in the period 2013-2015 and zero otherwise.

3.4.2.2 Dependent variables

After the completion of the Foundation Programme, doctors in the UK can apply to any of the sixteen specialties from Table 3.2. The specialty allocation process is made up of at least two recruitment rounds, however we limit the analysis to the first recruitment round. In further rounds, doctors' choice set is restricted to the training positions that have not been taken in the first round and therefore doctors' specialty choices are conditioned on the choice set available.

Ideally, we would report the effects of sorting and selection for each of the specialties in Table 3.2 individually; however we discard this option due to the limited sample size for some of the specialties. Instead we group specialties according to potentially important characteristics. We refer to the different possible groupings as domains and we consider three; the allocation of specialties to categories within these domains is

[12]Top 5 Medical Schools in the period 2013-2015 according to the Guardian Ranking: Cambridge, Oxford, Edinburgh, University College London and Dundee.

also set out in Table 3.2.

Domains of specialty

Using the domains, we are able to estimate how personal characteristics influence doctors' application patterns regarding: specialties monetary aspects, through the *income domain*, and specialties non-pecuniary attributes through the *pathway domain* and *practice domains*.

In the first domain, the *income domain*, we distinguish between specialties that have traditionally been associated with higher or lower earnings by doctors. Sorting of doctors according to their characteristics within this domain will have the effect of establishing an income gradient across socio-demographic characteristics. Thus, for example if female doctors are sorted and selected into low income specialties, we will subsequently observe that the earnings of female doctors are lower than their male counterparts. Morris et al. (2008) provide data on NHS and private income from consultants in England. We use that information to classify specialties in the top 25% in the distribution of total income as high income. Hence the dependent variable *TopInc* takes value one if the individual i applies to a top income specialty and zero otherwise. Similarly, specialties in the bottom 25% in the distribution of total income are classified as bottom income and the dependent variable *BottomInc* takes value one if the doctor i applies to a bottom income specialty and zero otherwise. This analysis connects with the traditional literature on specialty choice as we study the sorting of doctors with respect to the returns associated the different specialties.

We next distinguish between run-through and uncoupled specialties, which we refer to as the *pathway domain*. This distinction captures the potential for differential application behaviour between more or less *certain* career paths. Sorting and selection is this domain may be informative of the attitudes to career uncertainty on the part of doctors, with those wishing for, or being more suited to, a more pre-determined outcome opting into or being selected for run-through specialties. The variable *RunThro* takes value one if the individual applies to a run-through specialty and zero otherwise.

Third, we focus on *practice domain* as specialties can be classified along several axes regarding the type of doctor-patient interaction and the nature of interventions.

We group specialties into (i) surgical and non-surgical following Gagné and Léger (2005) and (ii) into primary care and non-primary care following Bazzoli (1985). The *practice domain* is multi-faceted, as there are also elements of professional prestige, competitiveness, that distinguish those groups of specialties. We do not make any judgments about these differences but note that it is likely to be of on-going concern if observable characteristics are correlated with a clear sorting or selection into this practice domain. In this case, the variables *Surgical* and *PrimaryC* take value one if the doctor has applied to a surgical or primary care specialty, respectively, and value zero otherwise.

Number of applications

As described in the conceptual framework, the number of applications made can be informative regarding doctor's perceptions of success and can affect the outcomes of the specialty allocation process. We define the variable *AppliMore* to take value one if the doctor has made more than one application, and zero if the total number of applications equals one. We conjecture that individuals who make a unique application might be reflecting a higher degree of self-confidence and as result devote more time and effort into its preparation, which in turn might lead them to better shortlisting and interview outcomes and hence a higher probability of receiving an offer.

Limitations

UKMED data does not include doctors who completed their medical studies outside the United Kingdom and therefore we cannot observe non-UK qualified doctor's recruitment outcomes. According to the General Medical Council (2013b), a quarter of the doctors in specialty training graduated from a foreign university. Nonetheless, the importance of omitting these doctors is partially offset by the secondary role non-European qualified doctors play in the specialty recruitment process. Non-European doctors only have access to training posts that have not been taken previously by UK graduates in the first recruitment round (British Medical Association 2017).

Due to UKMED data being a combination of administrative records and survey responses, missing data are common. A complete consideration of missing data issues is beyond the scope of this chapter. We approach the potential problems pragmatically and as a first step we explored the potential patterns of missing data and found little evidence that the probability of missing data on a specific variable depended on its own values or on the values of other variables in the data set. Hence we proceed as if data is missing completely at random (MCAR) and base our analysis on a sample of complete observations.

3.4.3 Econometric model and empirical implementation

Following the conceptual framework described in Section 3.3, doctors will apply to the specialty(ies) that yield the maximum net benefit B_{ji} weighted by the perceived probability of obtaining a training post in specialty j, P_{ji}.[13] The weighted net benefit is represented by A_{ji} that we define as a latent continuous variable that satisfies equation (3.1).

$$A_{ji} = Z_i^{'}\beta_j + \mu_{ji} \tag{3.1}$$

Where $Z_i^{'}$ is a vector of doctor's characteristics affecting the specialty choices, β_j is the vector of parameters that we want to estimate and μ_{ji} is the error term. However, the latent variable A_{ji} is unobservable and instead for each specialty j and doctor i we only observe whether an individual has applied or not to the specialty j. That relationship is captured by variable y_{ji} that takes value one if the doctor i has applied to specialty j and zero otherwise. Expression (3.2) shows this relationship.

$$y_{ji} = \begin{cases} 1 \; if & A_{ji} \geq 0 \\ 0 \; if & A_{ji} < 0 \end{cases} \tag{3.2}$$

We estimate the probability of doctor i applying to specialty j controlling for the vector of individual characteristics $Z_i^{'}$ by means of a Probit Regression as shown by the following expression:

$$P(y_{ji} = 1) = P(Z_i^{'}\beta_j + \mu_{ji} \geq 0) = P(-\mu_{ji} \leq Z_i^{'}\beta_j) = \Phi(Z_i^{'}\beta_j) \tag{3.3}$$

[13] Although the P_{ji} is defined in the conceptual framework as a function of doctors' characteristics and the capacity associated with each specialty, we do not include the latter in our empirical analysis. Capacity is constant for all doctors applying in a given year and although we have specialty allocation outcomes for more than one year, the variation is minimal and therefore its effect cannot be identified.

Where $\Phi(.)$ is the cumulative distribution function of the error term that we assume is independently and identically distributed and follows a standard normal distribution. However, as the variance of the error term μ_{ji} might suffer from heteroscedasticity we relax the identical distribution assumption and estimate robust standard errors.

The estimated parameters from the Probit model do not have a straightforward interpretation as, unlike the linear probability regression model, its estimates are not equivalent to the marginal effect of a covariate in the estimated probability. The marginal effect of a covariate k in the Probit model is given by (3.4) where $\phi_i(Z_i^{'}\beta)$ is the probability distribution function associated with $\Phi(.)$. As the marginal effect of one covariate depends on all the parameters and on the actual values of the vector of covariates we compute instead the average marginal effect (AME). The AME is computed for the average value of all the explanatory variables ($\bar{Z}_i$) including Z_k.

$$\frac{\partial P\left[y_{ji}|Z_i\right]}{\partial Z_{k_i}} = \frac{\partial \Phi(Z_i'\beta)}{\partial Z_{k_i}} = \phi_i(Z_i^{'}\beta) * \beta_k \tag{3.4}$$

Empirical implementation

We analyse six different outcome variables, y_j, that result from grouping the specialties according to the domains described in Section 3.4.2.2: (i) run-through vs. uncoupled specialties, (ii) 25% top income specialties vs. others, (iii) 25% bottom income specialties vs. others , (iv) surgical vs. non-surgical specialties, (v) primary care vs. non-primary care and (vi) multiple applications vs. single application.

We estimate three different specifications of equation (3.3), the main difference between these being the number of covariates included in the analysis. We face a trade-off between the number of covariates we can include and the number of observations available; a complete case analysis leads to a reduced sample size since there are variables with a large number of missing values. Table 3.3 sets out the variables included in each specification. Specification (1) includes the demographic, socioeconomic, part of the academic covariates and the year fixed effects, in order to assess the effect of medical and foundation school, Specification (2) includes them as covariates. Specification (3) adds the variable *UKCAT Score* to control for previous educational attainment. In addition, as a robustness check we perform an identical analysis to that described above to the reduced sample of doctors who only applied to one specialty (i.e. those for whom *AppliMore* equals zero). The objective is to disentangle whether socio-demographic characteristics affect differently the sample of doctors who made a single application.

In Table 3.3, specifications marked with an asterisk only apply to the dependent variable *AppliMore*. Specification (1*) includes the same covariates as specification (2) whilst specifications (2*)-(6*) control for specialty fixed effects.

3.4.4 Results: application stage

3.4.4.1 Descriptive statistics

Table 3.4 shows the descriptive statistics for three groups: UKMED population, the sample of doctors who participate in the application stage (*Sample 1- All doctors*) and the reduced sample of doctors who only apply to one specialty (*Sample 2- Single application*). The UKMED population size is 13,745 and includes all doctors who started medical school in UK during 2007 and 2008. Nonetheless, the size of *Sample 1* is 7,630 as we cannot include the doctors who have not participated in the specialty allocation process yet. We conjecture that the large discrepancy between the UKMED population and *Sample 1* size is due to differences in the duration of medical undergraduate[14] studies as different programmes have different lengths or can be done on a part-time basis.[15] In addition, medical students who have taken the option of intercalating[16] a course from a different subject would have extended the duration of studies at least one year. We observe that 66.6% of doctors in *Sample 1* started medical studies in 2007 whilst the share is 50.7% in the UKMED population. The latter is to be expected as in 2015, last year of data in our sample, many of the individuals who started medical school in 2008 may have not reached the stage of starting the specialty allocation process yet.

The descriptive statistics for the demographic variables (*Sample 1*) show that 58.1%

[14] There are two main types of undergraduate medical programs: regular, which last for five or six years, and graduate entry programmes, which last for four years and are designed for students who have already graduated from a different university degree.

[15] Foundation Training can be also done on a part-time basis and therefore doctors who did it part-time will take more than two years to complete it.

[16] As part the medical studies, individuals have the option to do an intercalating degree, which is time out of their regular medical degree to study a specific area of interest. In some cases intercalating could lead to medical students receiving an additional degree, on top of their undergraduate medical degree, and getting extra points in their application to a Foundation Training programme.

of doctors in the sample are *Woman*, 32.2% are *BME* and that the average age at which a doctor chooses their specialty is 27.7 years. The socioeconomic covariates show that 4.1% of the doctors grew up in a low-participation neighbourhood and 9.8% in a non-UK neighbourhood. Descriptive statistics for *School*, also a proxy for doctor's socioeconomic background, show that 21.3% of doctors attended an independent school, 63.9% a state school and 14.8% an unknown school type. The descriptive stats for the UKMED population show a slightly larger percentage of doctors attending an independent school, 24.3%. However, the percentage of doctors attending independent schools is considerably smaller than that reported in Chapter 2 for the NTS 2013 cohort. We conjecture that a large proportion of the responses associated with the category unknown school must correspond to doctors who attended an independent school. The variable *Parent Doctor* shows that 11.3% of the doctors have a parent who is also a medical doctor and 12.7% for the UKMED population.

The descriptive statistics for the academic variables show that 26.6% of doctors were *Graduate* upon entry. This group is over-represented in *Sample 1*, there are 18.3% in the UKMED population, reflecting that most of the graduated upon entry doctors have participated in the shorter medical undergraduate programme. The descriptive statistics for *UKCAT Score* show that on average the results for the UKMED population are slightly better than for the individuals in our sample, those are 25.2 vs. 25.1. Descriptive statistics for the variable *Top 5 Uni* show that 12.3% of individuals in *Sample 1* went to a top 5 university whilst it is 13.5% for the UKMED population.

Regarding the outcome variables from the application stage, 58.9% of the doctors apply to a run-through specialty, 10.9% to a top income, 14.3% to a bottom income, 53.0% to a primary care and 20.4% to a surgical specialty. The descriptive statistics from the interaction terms suggest that women apply in a higher proportion than men to *RunThro*, *PrimaryC* and *BottomInc* specialties. By contrast, *BME* doctors apply in a higher proportion than white doctors to *TopInc* and *Surgical* specialties. The descriptive for the variable *AppliMore* shows that 29.4% of doctors make more than one application. The interaction term for ethnicity show that 11.1% of *BME* doctors and 18.3% white doctors make more than one application. *BME* doctors make on average more applications than white doctors; if application patterns were similar for both groups we were to observe that only 9.4% *BME* would make more than one application. *AppliMore* seems to be evenly distributed with respect to doctor's gender.

The descriptive statistics for *Sample 2 - Single application* show little variation with respect to the observed for *Sample 1 All doctors*.

3.4.4.2 Estimation results

We present six tables with estimation results one for each of the six dependent variables we analyse. Each table reports the estimated coefficient ($\hat{\beta}$), the robust standard error (SE) and the average marginal effect (AME) for the three specifications analysed. We report and comment on the estimation results from specification (2), unless the variable of interest comes from a different specification. Moreover, in each table we present the results for the sample with all doctors who participated in the application process, i.e. *Sample 1- All doctors*, and the reduced sample that we use as robustness check, i.e. *Sample 2 - Single application*. Moreover, Figure 3.3 offers a summary of the estimation results for the dependent variables (i)-(v).

Figure 3.3: Summary of estimation results: application stage

	Run-Through ($Y_i = 1$)	Top-Income ($Y_i = 1$)	Bottom-Income ($Y_i = 1$)	Surgical ($Y_i = 1$)	Primary Care ($Y_i = 1$)
Woman	+	-	+	-	+
Age Process	+	-			+
Time Elapsed		-	+	-	
BME	+	+	-	+	+
Parent Doctor	-	+		+	+
POLAR3: Low Participation					
POLAR3: Non-UK	-			+	-
School: Independent					
School: Unknown					
Graduate		+			
UKCAT Score*	-		+		-
Top 5 University*	-				-

+/- indicates that the estimated effect is positive/negative and statistically significant at least at the 90% confidence level

The sign and significance reported correspond to the Probit estimates from Sample (1)- Specification (2)

Estimates for the variables marked with * come from a different specification (see Table 3.3)

Run-through vs. uncoupled specialties

The results displayed in Table 3.5 refer to the *pathway domain* where the dependent variable *RunThro* takes value one if the individual applies to a run-through specialty and zero if the individual applies to an uncoupled specialty.

Results for the demographic variables show that the variable *Woman* has a positive and statistically significant effect on the probability of choosing a run-through specialty. The average marginal effect indicates that being a female doctor increases the probability of choosing a run-through specialty by 0.148. The latter is consistent with the findings from Nicholson (2002). *BME* doctors seem to have a preference for run-through specialties, and the magnitude of the average marginal effect is 0.084. Similarly, the estimates for *Age Process* present a positive sign and the marginal effect indicates that being one year older increases the probability of choosing a run-through specialty by 0.010. All three effects are statistically significant at the 99% confidence level.

From the socioeconomic variables, we observe a negative and statistically significant effect of the category Non-UK neighbourhood, from the variable *POLAR3*, with respect to the base outcome (which is any other non-deprived neighbourhood) and the marginal effect is -0.060. The variable *Parent Doctor* also presents a negative effect with the average marginal effect of 0.038, significant at the 95% confidence level. No significant effects were found for the *School* variable.

Regarding academic variables (see specification (3)), the variable *UKCAT Score* shows a negative and statistically significant effect at the 99% confidence level. This implies that the larger the score is the lower the probability of choosing a run-through specialty. The average marginal effect suggest that an increase of one standard deviation in *UKCAT Score*, 2.23, reduces the probability of applying to a run-through specialty by approximately 0.029. The variable *Top 5 Uni* is also negative and statistically significant at the 99% confidence level; therefore doctors who have attended a top ranked medical school are less likely to apply to a run-through specialty, being the marginal effect -0.047. The breakdown of the effect of *Medical School* shows that doctors graduating from Hull-York, Leicester, Manchester or Peninsula are more likely to apply to *RunThro* than those who graduated from Birmingham which is the base outcome.

The estimates from *Sample 2* present the same signs and significance as those from *Sample 1*. By contrast, the magnitudes of those effects are slightly different for the variables *Woman* and *BME* that present a larger and smaller effect, respectively.

Top income specialties vs. all others

Table 3.6 shows the estimation results for the dependent variable *TopInc* that takes value one if the individual applies to a top income specialty, i.e. those in the top 25% in distribution of total income, and zero otherwise.

Estimation results show that female doctors are less likely to apply to a high-income specialty and the effect is statistically significant at the 99% confidence level. The average marginal effect suggests that the magnitude of the reduction in the probability of applying is 0.094, other things equal. The variables *Age Process* and *Time Elapsed* are also negative and statistically significant at the 95% confidence level. The AME suggests that every year older a doctor is reduces the probability of applying to a top income specialty by 0.003, whilst incrementing by one year the time elapsed between obtaining the primary medical qualification and participating in the specialty allocation process reduces the probability of applying to a top income specialty by approximately 0.035. The effect of *BME* is positive as minority ethnic doctors are more likely to apply to a top income specialty with an AME equal to 0.025.

Regarding socioeconomic variables, we find a positive and significant effect at the 95% confidence level for the variable *Parent Doctor*. On average having a parent who is also a doctor increases the probability of choosing a top income specialty by 0.025. The effect of attending an independent school seems to contribute to the selection of a highly income specialty but the effect is not significant in every specification. No significant effects were found for the neighbourhood deprivation variable *POLAR3*.

The estimation results for the academic covariates show that being a *Graduate* upon entry has a positive effect on the probability of choosing a *TopInc* specialty, with an AME equal to 0.023. No effects were found for the variable *Top 5 Uni*. Doctors who graduated from Barts, Hull-York, Norwich, Oxford and Peninsula are less likely than graduates from Birmingham to apply to a top income specialty.

The estimates from *Sample 2* present the same signs and significance as those from *Sample 1*. By contrast, the magnitudes of those effects are slightly larger for the variables *Woman*, *BME*, *Parent Doctor* and *School:Independent*. The latter is now statistically significant at the 95% confidence level.

Bottom income specialties vs. all others

Table 3.7 shows the estimation results for the dependent variable *BottomInc* that takes value one if the individual applies to a bottom income specialty, which are those that lay in the bottom 25% of the distribution of total income, and zero otherwise.

We find a positive effect in the probability of applying to a *BottomInc* specialty for the variable *Woman* and a negative effect for *BME*, both effects are statistically significant at the 99% confidence level. Being a female doctor increases the probability of applying to a bottom income specialty by 0.053 whilst being a minority ethnic doctor decreases the probability by approximately 0.031. These estimates present opposite signs to the estimates for *TopInc*, however these are of a smaller magnitude. Our findings for gender and ethnicity are consistent with the analysis done by Nicholson (2002) who found that female and white doctors were less likely to report relative income as the attribute that had major influence on their specialty choices.

None of the socioeconomic covariates is statistically significantly different from zero. Regarding academic variables, the estimate for *UKCAT Score* is positive and statistically significant at the 99% confidence level. The effect of an increase of one standard deviation (2.23) augments the probability of choosing a bottom income specialty by approximately 0.013. Medical school dummy variables, apart from Peninsula that has a negative significant estimate, do not show statistically significant effects.

Surgical specialties vs. non surgical

Table 3.8 shows the estimation results for the dependent variable *Surgical* that takes value one if the individual applies to a surgical specialty, and zero otherwise.

The estimates show that female doctors are less likely to apply to surgical specialties, the average marginal effect being 0.070 and statistically significant at the 99% confidence level. Doctors' age has a negative effect, the AME indicates that each year older a doctor is reduces the probability of of applying to a surgical specialty by -0.004 and the efffect is statistically significant at the 95% confidence level in specification (3). The variable *Time Elapsed* is also negative and statistically significant at the 99%

confidence level. The latter indicates that doctors who take an extra year to complete Foundation Training reduce their probability of choosing a surgical specialty by 0.059. Results for age and gender are consistent with the estimates from Gagné and Léger (2005) and Bhattacharya (2005). Lambert et al. (2006) also found that UK female doctors were less likely to choose a career in surgery. Gagné and Léger (2005) suggest that negative estimates for age are linked to the fact that older doctors have a shorter professional life and therefore have less time to recover the expenses from the long training period associated with surgical specialties. This is likely to be the case in the UK as well where surgical specialties take on average eight years of specialty training, the maximum length of training. The remaining demographic covariate, *BME*, presents a positive and significant effect at the 99% confidence level and has an average marginal effect associated equal to 0.063.

Regarding the socioeconomic covariates, the only positive and statistically significant effects are found for the variables *Parent Doctor* and *POLAR3:Non-UK neighbourhood*. The effect of having a parent who is also a doctor increases the probability of applying to a *Surgical* specialty by 0.032, whilst growing up in a non-UK neighbourhood increases that probability by approximately 0.075.

The estimates for the academic variables are statistically significant for *Graduate* and *UKCAT Score*, but only at the 90% confidence level. Estimates from specification (3) indicate that the associated AMEs are 0.026 for *Graduate* and -0.004 for *UKCAT Score*. With regard to *Medical School*, where Birmingham is the omitted category, the only statistically significant results are found for Hull-York, which presents a negative AME equal to -0.077, and for Imperial that presents a positive AME equal to 0.071.

The results for *Sample 2* are similar to the results from the complete sample. The main differences are that the variable *Age Process* becomes statistically significant in every specification whilst the estimates for *Time Elapsed* reduce their significance to a 90% confidence level. The effect associated with the variable *BME* is still statistically significant, however the AME is of a smaller magnitude. Finally, the socioeconomic variable *School:Independent* becomes statistically significant, with an AME of 0.029.

Primary care vs. non-primary care specialties

Table 3.9 shows the estimation results for the dependent variable *PrimaryC* that takes value one if the individual applies to a primary care specialty, and zero otherwise.

We find a positive effect in the probability of choosing a primary care specialty for both *Woman* and *BME* doctors, both effects are statistically significant at the 99% confidence level. The AME for *Woman* is 0.178 and 0.055 for *BME*. The magnitude of the effect of being a female doctor is considerable and our estimate is consistent with the findings from Lambert et al. (2006), Nicholson (2002) and Bhattacharya (2005). The two latter papers find opposite results to ours for ethnicity, however both studies compare black vs. white doctors in the US specialty market. In UKMED, *BME* variable includes other minority ethnic groups, Asian doctors being the largest category. The latter linked to the fact that the two countries have very different medical systems which make the results for ethnicity not directly comparable. By contrast, Bazzoli (1985) did not find a significant effect for *Woman* nor for *BME*. The variable *Age Process* has a positive sign and it is statistically significant at the 99% confidence level. Every year older a doctor is augments the probability of applying to *PrimaryC* by 0.011. This is consistent with the estimates reported by Hurley (1991).

With respect to the socioeconomic covariates, we find that having a parent who is also a doctor reduces the probability of applying to a *PrimaryC* specialty by 0.052, being the effect statistically significant at the 99% confidence level. This result concurs with Bazzoli (1985) who found that doctors whose parents have tertiary education are less likely to choose a primary care specialty. Those doctors who grew up in a non-UK neighbourhood are also less likely to choose a primary care specialty. The AME is equal to -0.113 and significant at the 99% confidence level.

The estimation results for the academic variables suggest that doctors who attended a *Top 5 Uni* medical school are less likely to apply to a primary care specialty, the AME is -0.068 and statistically significant at the 99% confidence level (specification (1)). The variable *UKCAT Score* has a negative coefficient estimate and is statistically significant at the 99% confidence level (specification (3)). The effect of an increase of one standard deviation (2.23) reduces the probability of choosing a primary care specialty by approximately 0.033. Nicholson (2002) found similar results for MCAT, the medical college admission test in the US. For *Medical School*, we find that doctors who graduate from Barts, Hull-York, Leicester, Newcastle, Peninsula and Sheffield are more likely to apply to a primary care specialty with respect to those who graduated from Birmingham. In contrast, the estimated effect associated with graduates from Cambridge is negative. The latter is consistent with the negative relationship between Oxbridge medical graduates and their propensity to apply to primary care specialties found by Goldacre et al. (2004).

Finally, the results for the *Sample 2* are similar in sign and magnitude to the described above for the complete sample.

Number of applications

Table 3.10 shows the estimation results for the dependent variable *AppliMore* that takes value one if the individual applies to two or more specialties, and zero if only applies to one.

The estimates for the variables *BME* and *Age Process* are positive and statistically significant in every specification. Ethnic minority and older doctors are more likely to make more than one application, even after controlling for specialty fixed effects. The AMEs from specification (1) are 0.059 for *BME* and 0.006 for *Age Process* both significant at the 99% confidence level. With respect to gender, we find that female doctors who apply to a *RunThro* (AME -0.028) or *PrimaryC* (AME -0.028) are less likely to make more than one application whilst those females applying to *Surgical* (AME 0.019) are more likely to make more than one application, with respect to male doctors applying to same options. The effect of the variable *POLAR3: Non-UK* is also positive and statistically significant in every specification. No other significant effects were found for the other socioeconomic covariates.

3.4.5 Discussion

Evidence in respect of selection by doctors in regard to their applications is very strong. The estimation results for the *income domain* show that female doctors select into low-income specialties and avoid high-income specialties, a situation that may contribute to the perpetuation of the gender wage gap in the medical profession.[17] On

[17]According to Rimmer (2017) the gender pay gap has grown over the past decade. In 2006, female doctors working full tuime earned 24% less than their male colleagues whilst female doctors in 2016

the contrary, ethnic minority doctors select into applying for high-income specialties and away from low-income ones. The fact that BME doctors in our sample come from wealthier backgrounds than the typical doctor might explain their inclination for top income specialties (see Table 3.14). Evidence regarding socioeconomic variables is weak, but we establish that having a parent who is also a doctor is associated with a higher probability of applying to high-income specialties. The latter might be reflecting the advantage in terms of knowledge of having a parent who is also a doctor. It may also indicate some degree of nepotism, as in Lentz and Laband (1989) who, after controlling for intergenerational transfers of human capital and other confounders, found that children of doctors were 14% more likely to be admitted to medical schools in the US.

Nonetheless, the percentage of doctors who attended an independent school in the UKMED sample is considerably smaller than the figures reported in Chapter 2 for the NTS 2013 cohort. We conjecture that a large proportion of the responses associated with the category *School:unknown* should correspond to doctors who attended an independent school instead. Moreover, doctors who attended an independent school are also underrepresented in our sample of analysis (*Sample 1*) with respect to the UKMED population. The latter suggest that socioeconomic privileged doctors are more likely to have done a longer medical undergraduate programme, have done extra clinical training or have intercalated another degree as they are more likely to be able to afford the opportunity costs of delaying their entry to the job market. All those extracurricular activities are very likely to increase their chances of being admitted to the most demanded specialties.

The results regarding the *pathway domain* show that women, older doctors and bottom achievers are more likely to choose a run-through specialty. We conjecture that choosing a run-through specialty can be interpreted as a less risky and more stable choice since doctors only need to take part in the specialty allocation once for the whole period of training. Moreover, most run-through specialties present shorter training periods and might be easier to combine with part-time work and therefore be preferred by those doctors looking for a better work-leisure-family balance.

earn 34% less.

The estimation results for the *practice domain* show that females and older doctors are less likely to choose a surgical specialty whilst BME doctors and those who have a parent who is also a doctor present a higher probability. Results for primary care specialties are the opposite as female doctors, older doctors and also BME doctors are more likely to apply to a primary care specialty. On the contrary, having a parent who is also a doctor, having attended an independent school or a top ranked university reduce the probability of applying to a primary care specialty. In general, these findings suggest that the allocation of doctors with respect to their socioeconomic background observed in Chapter 2 is largely driven by their application behaviour as doctors from privileged socioeconomic backgrounds are more likely to apply to a surgical specialty and less likely to a primary care specialty than doctors coming from non-privileged backgrounds. That behaviour might be reflecting the fact that socioeconomic privileged doctors might place a higher value into the specialties' monetary attributes than doctors from worse-off backgrounds. Then, policy interventions aimed at widening the access to the medical profession to individuals from more deprived socioeconomic backgrounds could to some extend reduce the shortages in primary care specialties.

In this section of Chapter 3, we also explore the impact of doctors' socio-demographic characteristics on the number of applications a doctor makes. This analysis is novel and suggests that the number of applications a doctor makes depends on the specialties the doctor applies to. However, the main finding is that BME doctors present a different application strategy to white doctors. They make more applications and that effect remains significant even after controlling for medical school effects, other previous educational attainment and specialty fixed effects. According to our conceptual framework, other things being equal, that behaviour might be detrimental for BME in the selection stage. Section 3.5 analyses the determinants of interview score and will shed light on the effect of application behaviour on selection outcomes.

Our analysis is based on the observed outcomes from the medical specialty application stage in the UK. According to our conceptual framework application decisions are determined by a combination of the net benefit associated with specialties and the perceived probability of getting access to them. With the data available we cannot disentangle the effect of doctors' sociodemographic characteristics in each of these elements separately. Future research should have access to stated preferences by asking doctors for their preferred specialties, irrespective of their probability of getting access to them, and to find how different those are from the observed choices from the application process. We would be able to achieve a better understanding of the role of perceived probability in determining doctors' application patterns and we would be able to examine whether it affects the different sociodemographic groups differently. Another avenue for future research could be to carry out a discrete choice experiment, similar to the work of Sivey et al. (2012) for Australia, to explore the trade-offs doctors are willing to make between specialties' monetary and non-monetary attributes. The latter becomes particularly relevant with the feminisation of the medical workforce in order to understand whether female doctors value those trade-offs differently.

3.5 Selection stage

3.5.1 Background

There is a desire for ensuring the equality, diversity and opportunity in the medical profession by promoting a fair, transparent and effective specialty recruitment process (General Medical Council 2010). In this section, we focus attention on the selection process that takes place after doctors have made their specialty application choices. The interview is the most decisive element of the selection stage. We analyse the role of doctors' ethnicity and gender in determining interview scores using the UKMED dataset and we test whether, other things being equal, ethnicity and gender do have a statistically significant impact on interview scores.

Previous research found evidence of ethnic biases and differential attainment of ethnic minorities in the British medical profession during the 1980s and 1990s. At the point of admission to medical school, McManus et al. (1995), McManus et al. (1998) and Arulampalam et al. (2005) found that ethnic minority candidates receive less entry offers than white candidates after controlling for previous educational attainment and other relevant characteristics. Several studies have analysed the relationship between ethnicity, gender and academic performance. Dillner (1995), McManus et al. (1996), Wass et al. (2003), Woolf et al. (2011) in undergraduate examinations and Dewhurst et al. (2007) and Woolf et al. (2011) in postgraduate clinical skill examinations found that the differential attainment of ethnic minorities is negative and statistically significant on both types of assessments and cannot be explained in terms of previous educational performance. Dewhurst et al. (2007) and Woolf et al. (2011) also tested the effect of gender in clinical skill examinations, finding that women were more likely to outperform men. Nonetheless, McManus et al. (2013) did not find evidence of ethnic or gender biases in examiners from postgraduate clinical skill assessments. The authors exploited the fact that examiners were always in pairs and compared the assessments of each examiner against a 'basket' of all co-examiners. Wass et al. (2003) associate the differential attainment to differences in styles of communication, values and ways of learning of ethnic minority doctors.

After qualification from medical school the observed differential attainment continues. McKeigue et al. (1990) showed that ethnic minority doctors reported lower success rates in obtaining specialty posts[18] with respect to white British doctors. Similarly, Esmail and Everington (1993) in a small experiment, consisting of sending identical curriculum vitae, found that candidates with white sounding names were twice as likely to be shortlisted than those with foreign names. The cited studies analysed the outcomes of doctors in the 1980s when the process of selection into specialties was arranged locally, sometimes informally and subject to personal arrangements (McKeigue et al. 1990). In the mid-2000s there was a reorganization of the delivery of postgraduate medical training[19] with the objective of improving the quality of training, reducing uncertainty and minimizing the time to completion (Lewington 2012). The recruitment into specialties is now organized nationally, by the correspondent Royal College or a by a Local Educational Training Board (LETB) on behalf of all the other LETBs, and with the purpose of ensuring a fair, transparent and effective selection process (General Medical Council 2010). Currently, the typical interview of the specialty recruitment process is divided in a minimum of two interviewing stations and in each of these the candidate is evaluated by two interviewers independently. This style of interview, known as a multiple-mini interview, is more reliable and more consistent than the conventional interview methods (Knorr and Hissbach 2014; Patterson et al. 2016) and therefore it should have eliminated the ethnic biases observed in specialty recruitment in the UK in the past.

In this section, we analyse the interview scores of the doctors who started medical school in 2007 and 2008 and therefore we test whether the differential outcomes observed in the past for ethnic minority doctors faded with the reorganization and standardization of the processes that give access to postgraduate specialty training. We also test whether doctors' gender has any impact on the interview scores. We observe the interview score for 16 different specialties, which we transform to make comparable and perform a pooled analysis. First, we apply Ordinary Least Squares (OLS) linear regression where we control for demographic and socioeconomic covariates, measures of academic attainment and performance, medical school fixed effects, and other relevant characteristics. We find a significant and negative effect of being

[18] Before the modernization of medical careers in 2007, after medical school newly graduated doctors had to find a house officer post, so a few years later they could apply to specialty registrar posts.
[19] The plan is known as Modernising Medical Careers (MMC).

Black and Minority Ethnic (BME) and positive and significant effect of being female. Then, we apply a Oaxaca-Blinder (OB) (Oaxaca 1973; Blinder 1973) decomposition of differences in the mean interview score between groups. The OB decomposition indicates how much of the gap in interview scores can be explained by differences in the explanatory covariates between groups and how much cannot and may be, therefore, associated with discrimination. Our findings show that a statistically significant percentage of the observed differences remain unexplained.

Our study provides evidence regarding the functioning of the selection system and shows that BME doctors and men experience differential attainment in the selection process for specialty training. Our findings serve as the basis for further study of the causes of differential attainment and the identification of any necessary policy intervention.

3.5.2 Data and variables

The cross-sectional data used in this section are the same as those used to analyse the outcomes from the application stage. See Section 3.4.2 for a full description of the data. Similarly, Table 3.1 sets out all the demographic, socioeconomic and academic variables that we use as controls in the selection stage.

Dependent variables

Interview scores for different specialties use different scales and therefore are not comparable (see Table 3.11). Ideally, we would carry out a case-by-case analysis, but as in the application process, the small sample size associated with each specialty impedes this practice. In this case, instead of grouping similar specialties together as we do in the application process, we transform interview scores to make them comparable across specialties and carry out a joint analysis. We apply two different transformations represented by IS_{ji}^{T1} and IS_{ji}^{T2} where i represents the individual and j the specialty.

Expression (3.5) gives the first transformation we apply:

$$IS_{ji}^{T1} = \frac{IS_{ji} - IS_{j}^{Min}}{IS_{j}^{Max} - IS_{j}^{Min}} \in [0, 1] \tag{3.5}$$

The transformed interview score IS_{ji}^{T1} ranges from 0 to 1, a feature that facilitates its interpretation. In equation (3.5), IS_{ji} denotes the observed interview score of doctor i in specialty j. IS_j^{Max} and IS_j^{Min} indicate the maximum and minimum interview score observed in specialty j.

The second transformation consists of the standardization of the interview score as shown by (3.6), where μ_j^{IS} indicates the mean interview score in specialty j and σ_j^{IS} is the associated standard deviation. IS^{T2} follows a standard normal distribution and therefore scores under the mean become negative and over the mean positive. It should be noted that both transformations are also applied to the shortlisting score.[20]

$$IS_{ji}^{T2} = \frac{IS_{ji} - \mu_j^{IS}}{\sigma_j^{IS}} \sim \mathcal{N}(0,1) \tag{3.6}$$

A limitation of the first transformation is that the maximum and minimum interview score come from the data observed in our sample and they might not necessarily correspond to the global maximum and minimum interview score from the actual interview processes. We do not observe the interview scores of doctors who started medical school before year 2007 or after 2008 and might have participated in the selection processes that we analyse. Moreover, as described in Section 3.4.2, we do not observe specialty allocation outcomes for doctors who qualified outside of the UK. The same limitation applies to the mean and standard deviation used in (3.6).

We introduce *Specialty* dummy variables, one for each of the specialties on Table 3.11, to control for specialty-interview panel effects. Despite the standardisation of scores, it could be the case that the interview panel of one specialty may be granting upward biased scores whilst another specialty may be doing the opposite. The vector of *Specialty* dummies aims at capturing those disparities if they exist.

We observe the interview scores of 3,552 individuals who took part in 4,117 interviews; however, we limit our analysis to the 3,053 individuals who participated in a single interview process. As described in the conceptual framework, Section 3.3, effort

[20]

$$SC_{ji}^{T1} = \frac{SC_{ji} - SC_j^{Min}}{SC_j^{Max} - SC_j^{Min}} \in [0,1]$$

$$SC_{ji}^{T2} = \frac{SC_{ji} - \mu_j^{SC}}{\sigma_j^{SC}} \sim \mathcal{N}(0,1)$$

and resources devoted to prepare an interview may vary with the perceived probability of getting the position, the doctor's personal preferences, and the number of interviews the doctor will have, among other factors. Therefore, degrees of effort and preparation of doctors who have done two or more interviews may be different from those who only have done one. We conjecture that for the former group the analysis of each interview outcome in isolation may not constitute a true representation of a doctor's capabilities as they are splitting their endowment of time and effort into more than one option.

3.5.3 Econometric model and empirical implementation

Following the conceptual framework described in Section 3.3, selectors from specialty j will offer a specialty training post to the doctors who have associated the maximum values of the variable total score. The latter represented by TS_{ji} is a function of the shortlisting and interview scores, as given by $TS_{ji} = f(SC_{ji}, IS_{ji})$, and the weight given to each of those two elements varies from specialty to specialty. We follow a different strategy to the one applied in the *application* stage. Rather than analysing the likelihood of receiving an offer in a specific group of specialties, we focus on understanding how doctors' sociodemographic characteristics influence interview scores and hence how those characteristics can affect the likelihood of being offered a training post in any specialty.

OLS estimation

As a first step we regress the transformed interview scores, IS^{T1}, and IS^{T2} against a set of explanatory covariates by means of an Ordinary Least-Square (OLS) linear regression. The choice of the OLS is natural as both interview score transformations are continuous variables and most observations fall closer to the middle of the distribution rather than closer to the bounds.[21] Moreover, OLS estimates have a straightforward interpretation as the marginal effect of the covariate in the outcome variable. The

[21]The latter is especially relevant in the case of IS^{T1}, that only ranges from zero to one. The OLS model is more robust to misspecification than limited dependent variable models, such as Probit or Logit, however its estimates present the unboundedness problem. Nonetheless, we are interested in the direction of the effects and our objective is being able to directly compare the estimates from the two transformations and not utilising OLS estimates for forecast analysis.

relationship between interview score and the rest of covariates is represented by (3.7)

$$IS_i^{TN} = \beta_0^N + DE_i^{'}\beta_1^N + SE_i^{'}\beta_2^N + AC_i^{'}\beta_3^N + OS_i^{'}\beta_4^N + \mu_i^N, \quad N = 1,2 \tag{3.7}$$

Explanatory variables are classified into demographic ($DE^{'}$), socioeconomic ($SE^{'}$) and academic ($AC^{'}$) as Table 3.1 sets out. We also control for the features of the specialty allocation process, represented by the vector of variables $OS^{'}$, that include shortlisting score, the variable *AppliMore* that reflects doctors' application strategies and that we use as a proxy of doctors' effort (see Section 3.3), year fixed effects (i.e. *Year Process* and *Year Start*) and specialty-interview panel fixed effects.

The error term is represented by μ_i and by assumption its conditional mean should be zero, $E(\mu_i|X_i) = 0$, where X_i represents the joint vector of independent variables from individual i. The assumption refers to the exogeneity of the regressors and it is essential for consistent estimation of the vector β. The latter assumption together with the assumptions of conditional homoscedasticity, $E(\mu_i^2|X_i) = \sigma^2$, and conditionally uncorrelated observations, $E(\mu_i\mu_k|X_i, X_k) = 0, i \neq k$, ensure OLS estimators are fully efficient. However, we relax the homoscedasticity assumption and estimate heteroscedasticity-robust standard errors, following the method developed by White (1980), and therefore allowing the independent variables and the error term to not be necessarily identically distributed.

With respect to the empirical implementation, we face a trade-off between the number of independent variables we can include and the number of observations available to carry out a complete case analysis. We present the results for four different specifications that differ from each other in the number of covariates included. Table 3.12 sets out the covariates included in each specification.

Oaxaca-Blinder decomposition

As described in Section 3.5.1 there is evidence of ethnic and gender biases and differential attainment of those groups in different settings from undergraduate medical studies to postgraduate medical training. We apply Oaxaca-Blinder (OB) decomposition (Oaxaca 1973; Blinder 1973) to disentangle the sources of the ethnic and gender gap observed in specialty recruitment interview scores. This method has been extensively applied to the decomposition of gender and racial wage gaps as in Reimers (1983) and O' Neill and O' Neill (2006) but also in other settings like Ammermüller (2004) who used it to explain the gaps in PISA test scores between Finland and Germany.

Our objective is to measure how much of the overall gap in the mean interview scores is attributable to (i) differences in the observed characteristics rather than (ii) differences in the estimators (β). O' Donnell et al. (2008) refers to (i) as the *explained* component or differences in endowments whilst (ii) is commonly known as the *unexplained* component or differences in coefficients. We estimate how much of the differences in scores can be explained by group differences in academic performance, socioeconomic background, medical school and so on. The basis of the decomposition relies on the construction of a *counterfactual* outcome, that captures an hypothetical average interview score of BME doctors if they would have the same distribution of covariates characteristics as white doctors. The construction of the *counterfactual* works in a similar fashion for female and male doctors.

Expression (3.8) is a simplified version of (3.7) where Y_g represents the outcome variable, X_g the vector of explanatory covariates and $g \in \{a, b\}$ indicates the demographic group the doctor belongs to. In our analysis, a indicates white or male doctor, whilst b refers to BME or female doctor. Subscripts for the individual (i) have been dropped for ease of presentation. We are interested in the computation of the estimated mean outcome difference between groups a and b. That difference, D, is represented in (3.9) where $E(\beta_g) = \beta_g$ and $E(\mu_g) = 0$.

$$Y_g = X_g \beta_g + \mu_g \tag{3.8}$$

$$D = E(Y_a) - E(Y_b) = E(X_a)' \beta_a - E(X_b)' \beta_b \tag{3.9}$$

To identify the contribution of group differences in explanatory covariates to the overall observed differences in interview score expression (3.9) can be rearranged as follows (Jann 2008):

$$D = \underbrace{\{E(X_a) - E(X_b)\}' \beta^*}_{E} + \underbrace{\{E(X_a)'(\beta_a - \beta^*) - E(X_b)'(\beta_b - \beta^*)\}}_{U} \tag{3.10}$$

This is a *twofold* decomposition where the first component E is the part of the outcome differential that is explained by group differences in the predictors (i.e. the *explained* effect) and the second U is the difference in the estimator or *unexplained* effect. The latter can be interpreted as reflecting the existence of some form of discrimination. However, this interpretation requires the non-existence of relevant unobservable predictors affecting interview score. Moreover, even assuming the validity of the latter, it is not clear whether discrimination affects only one or both groups at the same time. The undervaluation of one group might come with the overvaluation of the other and vice-versa. For this reason we utilise benchmark coefficients $\beta^* = \Omega\hat{\beta}_a + (I - \Omega)\hat{\beta}_b$, where $\Omega = (X_a'X_a + X_b'X_b)^{-1}X_a'X_a$ and I is the identity matrix, that are equivalent to the coefficients from the pooled model and would be the ones resulting from a non-discriminatory interview process (Neumark 1988; Oaxaca and Ransom 1994).

The Oaxaca-Binder decomposition of the mean assumes the interview score model to be linear and separable in observable characteristics as represented in (3.8) and a zero conditional mean $E[\mu_g|X] = 0$ (Fortin et al. 2011). In addition, our groups of analysis are mutually exclusive and the fact that the formation of groups is exogenous, as sex and ethnicity are intrinsic to the individual, avoids problems of endogeneity and self-selection into groups.

The decomposition in practice consists of inserting the sample means and the OLS estimates of β_g and β^* in (3.10). We apply the procedure by means of the *Oaxaca* command for Stata developed by Jann (2008). The estimation of OB decomposition of the mean has some limitations in the presence of categorical variables. Those variables do not have a natural zero point and a different choice of the omitted group would yield different decomposition results. To address the issue, we transform the model restricting the coefficients for the single categories to sum zero following the solution proposed by Yun (2005). This solution comes at the expense of interpretability of the coefficients from the categorical variables (Fortin et al. 2011). Nonetheless, our main interest relies on the aggregate decomposition results that consists of the separation of D into its two components E and U and that it is not affected by the categorical variables interpretability issue. By contrast, the detailed decomposition that involves subdividing E and U into the respective contribution of each explanatory covariate to the explained and unexplained component would be indeed affected by the interpretability issue and for that reason not reported.

Robustness checks

We consider two types of robustness checks. First, we apply the OB decomposition separately to *Core Medical Training* and *Core Surgical Training* which are the two specialties with the larger number of observations for interview score (see Table 3.11). We check if the differences in means between groups still hold and that they are not the result of individuals self-selecting into the specialties, despite the inclusion of the specialty interview fixed effects our pooled results might be capturing. The second check we apply is the OB decomposition of the mean interview score of two artificially created groups where individuals were randomly allocated. The objective is to ensure that our findings are not the result of a statistical artefact.

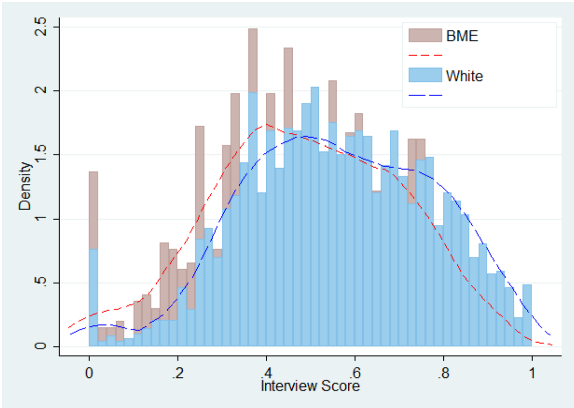
3.5.4 Results: Selection stage

3.5.4.1 Descriptive statistics

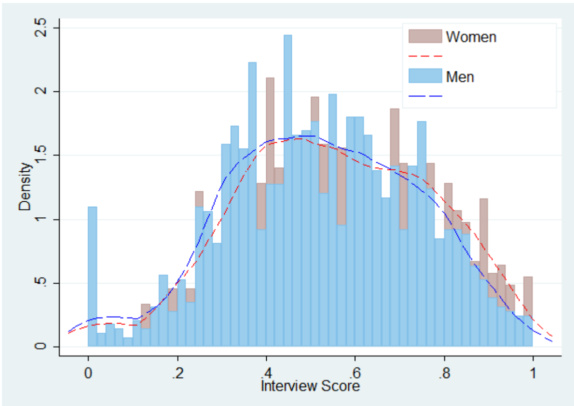
Table 3.13 show the descriptive statistics for the sample of 3,053 doctors who had a single interview between the years 2012 and 2015. We observe a predominance of women 53.7% and white doctors 67.7%. It also shows the descriptive statistics for the complete sample that includes the doctors who had more than one interview (N=3,552). The descriptive statistics do not display large differences in the explanatory variables between the two groups.

Table 3.14 shows the breakdown of descriptive statistics by gender and ethnicity. The comparison of the mean values of IS^{T1} highlights disparities between demographic groups. White doctors have a mean interview score of 0.56 whilst the mean is 0.49 for BME doctors. In the case of gender there are also differences, but of a smaller magnitude. The mean IS^{T1} for women is 0.55 and 0.52 for men. Figure 3.4 shows the kernel distribution of IS^{T1} by ethnicity and gender. The distribution of interview score IS^{T1} is fairly similar for male and female doctors, however it shows that men are over-represented in the left tail of distribution whilst women are over-represented on the right tail of the distribution. In terms of ethnicity, interview scores associated with BME doctors are concentrated in the lower values of the score distribution. The comparison of the mean values of IS^{T2}, that follows a standard normal distribution and shows a wider range than IS^{T1}, leads to differences between demographic groups in the same direction and similar magnitudes to that described above.

Figure 3.4: Kernel distributions of transformed interview score (IS^{T1}) by ethnicity and gender



(a) Ethnicity



(b) Gender

For shortlisting score (SC^{T1}) we observe a clear difference between white and BME doctors in the same direction as for IS^{T1} , however of a smaller magnitude, the associated means are 0.48 versus 0.44. No differences are observed for gender. Figure 3.5 shows that BME doctors are under-represented in the right tail of the shortlisting score distribution.

The variable *Age Process* shows that BME doctors are on average younger than white doctors, 27.5 versus 28.2, and that men are older than women, 28.1 vs. 27.8. The distribution of the socioeconomic covariates seems unbalanced across the groups of interest and suggests that on average BME doctors come from better-off backgrounds.

The proportion of BME doctors who studied in an independent school is larger than the proportion of white doctors, 20.5% versus 18.7%. Similarly, the percentage of white doctors who come from a deprived neighbourhood is larger than the proportion of BME doctors, 4.8% and 3.4%. The percentage of female doctors from a low-participation neighbourhood is 4.0% whilst it is 4.7% for male doctors. In our sample, 15.3% of BME doctors have a parent who is also doctor whilst it is 8.3% for white doctors.

BME doctors are less likely to hold another degree at the start of medical school than white doctors, 24.7% versus 38.9% and they are also less likely to have attended a *Top 5 Uni*, 11.1% versus 12.9%. The results for UKCAT test scores are fairly similar across groups: BME doctors and women have the lowest average test scores at 24.71 and 24.97, respectively. In relation to doctors' application behaviour, BME doctors make on average more applications than white doctors, 1.47 versus 1.34. Women in our sample also make more applications than men, 1.41 versus 1.34. Overall, we observe clear differences in both interview scores and control variables.

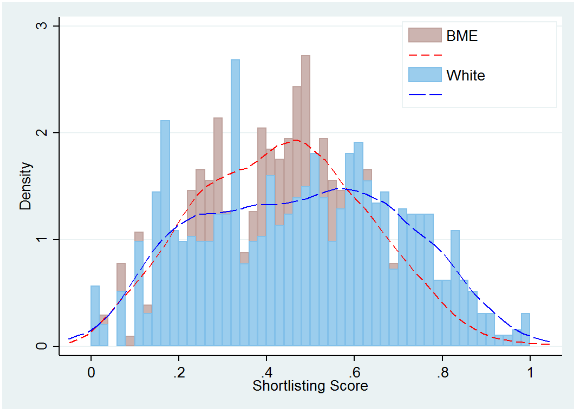
3.5.4.2 Regression estimates

OLS

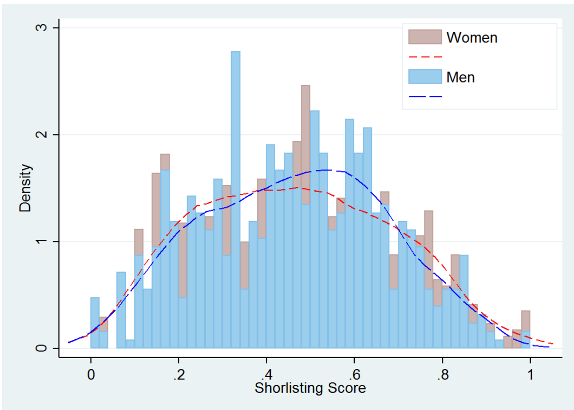
Table 3.15 shows the OLS estimates for the two transformations, $IS^{T1} \in [0, 1]$ and $IS^{T2} \sim \mathcal{N}(0, 1)$, applied to interview score. Results for gender and ethnicity are similar in sign and magnitude across specifications and yield very similar results for both transformations. In regard to the overall associations between interview scores and doctor's characteristics we find evidence of women scoring more highly than men and BME doctors scoring less highly than white doctors, other things equal. Estimates for both effects are statistically significant at least at the 95% confidence level in all specifications. The estimates of the first (second) transformation show a negative effect associated with BME doctors that ranges from -0.059 to -0.038 (-0.175 to -0.211) and a positive effect associated with being a female doctor ranges from 0.032 to 0.039 (0.117 to 0.125). The magnitude of the effects is not inconsiderable taking into account that $IS^{T1} \in [0, 1]$.

As expected, shortlisting score is a very good predictor of interview score. An increase of a standard deviation (0.216 as calculated in the full sample, see Table 3.13)

Figure 3.5: Kernel distributions of transformed shortlisting score (SC^{T1}) by ethnicity and gender



(a) Ethnicity



(b) Gender

in SC^{T1} increases IS^{T1} by approximately 0.051. We find similar results for UKCAT scores, however they are of a smaller magnitude as the increase of one standard deviation (2.253) increments the interview score by 0.015. The variable *AppliMore* has a negative sign, as expected. Making an additional application, and therefore dividing the endowment of time and resources into another option, reduces the interview score approximately by 0.03. However, the statistical significance of the effect diminishes after controlling for shortlisting score, see specification (3) and (4). In terms of socioeconomic covariates, we only find a negative statistically significant estimate associated with being raised in a non-UK neighbourhood, variable *POLAR3:Non-UK*, however the effect becomes not significant after controlling for shortlisting score. Similarly, we observe a positive impact on interview scores associated with being a graduate at the point of entry to medical school that becomes not significant with the inclusion of the shortlisting score. Although the effect of the variable *School:Independent*, one of the proxies for socioeconomic background, is positive it is not statistically significant. Having a parent who is also a doctor does not seem to affect the interview scores. The estimate for the variable *Top 5 Uni* is positive but not statistically significant.

Entering medical school in 2008 has a negative effect and suggests that those individuals who started in 2007 are more likely to achieve higher interview scores. In our sample, 73% of doctors started medical school in 2007. This result reflects the fact that doctors from the 2007 cohort are more likely to have done the long undergraduate medical degree, and also had an extra year during which they could have intercalated a course from a different field, had more time for volunteering and for doing extra clinical training, among other things. Therefore, we conjecture the combination of all those elements is translating to better interview outcomes.

Oaxaca-Blinder decomposition

OB ethnicity

Table 3.16 shows the results for the aggregate OB decomposition by ethnicity for the two transformations applied to interview score. Estimates are similar in sign and magnitude across specifications and transformations. We find statistically significant differences of mean interview scores between white and BME doctors. Before controlling for *shortlisting score* (see specification IS^{T1}(2)) the total difference is 0.073. The difference, given by $E(Y_{White}) - E(Y_{BME})$, is divided into *explained* and *unexplained*, effects that account for 0.018 and 0.055, statistically significant at the 95% and 99% confidence level, respectively. Estimates from specification IS^{T1} (3) include the variable *Shortlisting score* at the expense of reducing the sample to 1,479 doctors and the estimated difference becomes larger and is equal to 0.082. The breakdown of the difference indicates that the *explained* effect for this sample, after controlling for interview score, is larger and equal to 0.036 whilst the *unexplained* effect is slightly smaller and equal to 0.046. The latter accounts for more than half of the total differences in mean score between white and ethnic minority doctors. According to the estimates from specification IS^{T2} (3) the *unexplained* effect accounts for more than three quarters of the total difference.

Our results show that the different distribution of endowments between white and

BME doctors partly explains differences in the mean interview scores. Nonetheless, a considerable part remains unexplained, suggesting that not only the level of endowments is different but that those endowments are also priced differently (i.e. $\beta_{White} \neq \beta_{BME}$). The results for the detailed decomposition, not reported, suggest that the main contributors to the unexplained differences are medical school fixed effects, year effects and specialty panel fixed effects whilst the main contributors to the explained part are the same three plus the variables *Woman*, *AppliMore*, *Shortlisting score* and *UKCAT score*.

OB Gender

The results for gender in Table 3.17 confirm that the mean interview score for male doctors is smaller than for female doctors. The difference $E(Y_{Men})-E(Y_{Women})$ before controlling for shortlisting score equals -0.026 (see specifications IS^{T1}(1) and (2)). However, for specification (2) the *unexplained* effect is the only element statistically significant at the 99% confidence level and is equal to -0.033. The *explained* effect, although not statistically significant, is positive reflecting the fact that the differences in endowments favour male doctors and offset part of the negative effect associated with the *unexplained* component. The estimates in specification IS^{T1}(3) control for shortlisting score and are fairly similar to those from specification IS^{T1}(2). The total difference is -0.029 and significant at the 90% confidence level whilst the unexplained effect equals 0.031 and it is significant at the 95% confidence level. The estimates for IS^{T2} show similar signs and magnitude to those described for IS^{T1}.

The results for the detailed decomposition, not reported, suggest that the main contributors to the unexplained differences are medical school fixed effects, year effects and specialty panel fixed effects whilst the main contributors to the explained part are the same three plus the variables *BME* , *AppliMore* , *Shortlisting score* and *UKCAT score*.

3.5.5 Robustness checks

Tables 3.18 and 3.19 show the decomposition results for (IS^{T1}) for the specialties core medical training and core surgical training by gender and ethnicity. We find that the aggregate difference in means between BME and white doctors, despite the reduction in sample size, remains statistically significant and it is of a similar magnitude to the observed in the general OB decomposition. The results for gender present similar signs to the estimates from the general OB for gender, however they are no longer statistically significant.

The second check we apply is the OB decomposition of the mean interview score of two artificially created groups where individuals were randomly allocated. Table 3.20 shows the results. No statistically significant differences in means were found between the groups.

3.5.6 Discussion

We find strong evidence of BME doctors scoring less highly than white doctors in the interview that is pivotal in giving access to a specialty training position. We also find that female doctors score more highly than male doctors, however the effect is of a smaller magnitude and not statistically significant in every specification. These results remain after accounting for previous educational attainment and imply that, other things being equal, female and white doctors are more likely to be accepted into specialty training.

The results from the Oaxaca-Binder decomposition suggest that a large share of those differences remains unexplained, since they cannot be explained by the differences in the control variables between the demographic groups. Therefore, it seems that, despite all the measures implemented to standardize and regulate the recruitment into specializations, the interview process might be prone to some type of bias.

Since equality and gender are protected characteristics,[22] we rule out the existence of taste-based discrimination (Becker 1959) and conjecture that a large part of the unexplained differences may be the result of statistical discrimination phenomena, as described in Chapter 2. Interviewers may use observable characteristics from doctors like gender and ethnicity as proxy for unobservable, but outcome relevant characteristics.

Our sample descriptive statistics (Table 3.14) show that on average BME doctors have a lower shortlisting score than white doctors. Following Phelps (1972), in a situ-

[22]Equality Act 2010.

ation where interviewers are not able to observe a doctor's true ability, but do observe group identity, they could rely on group average signals of ability like shortlisting score and as a result BME doctors would receive lower interview scores. Another possibility is that the observed interview outcomes from BME doctors are the result of the *self fulfilling prophecy* described in Arrow (1973). Arrow's argument is that BME doctors might have some initial beliefs about their chances of gaining a training post, based on historical ratios, preconceptions, past taste-based discrimination, etc., and those are different from the beliefs of white doctors. In our sample, we observe that BME doctors make more applications than white doctors and, following Arrow's theory, it could be a way to ensure more options for obtaining a training post as they might have more pessimistic beliefs than white doctors. According to the conceptual framework, that behaviour implies the division of their endowment of time and resources into two or more applications. Selectors might perceive their lower investment into a single application, therefore giving BME doctors lower shortlisting and interview scores, other things equal. Another reason, also extracted from statistical discrimination literature, is related to cultural and language differences. According to Lang (1986), differences in different aspects of verbal and non-verbal communication may make assessments by mostly non-ethnic minority selectors of the performance BME doctors less accurate.

In the case of gender, the differences in interview scores are of a smaller magnitude compared to the differences found for BME and white doctors. The positive bias associated with female doctors could be explained by dissimilarities in practice between men and women. Tsugawa, Jena, Figueroa et al. (2017) and Wallis et al. (2017) show evidence that patients treated by female doctors had lower mortality and readmission rates than those treated by male doctors. Similarly, Baumhäkel et al. (2009) found that females are more likely to adhere to clinical guidelines, Cooper-Patrick et al. (1999) found that they have more participatory visits with their patients and Lurie et al. (1993) shows that female doctors provide preventive care more often than male doctors. The positive bias could be explained by the fact that selectors are aware of the positive outcomes described above and would grant women biased higher interview scores, other things equal. By contrast, the unexplained positive bias associated with female doctors might be reflecting a patronizing behaviour from selectors.

Our aim is to provide useful indications of particular hypotheses to be explored in more detail. We focus on the decomposition of differences in the mean of interview scores, however it would be useful to test if the gap is different in other parts of the distribution. For example, we could test if the gap in interview scores is larger in the upper part of the distribution as Figure 3.4 suggests. Future work, should go beyond the mean and apply a distributional method following the work of Firpo et al. (2009) and Chernozhukov et al. (2013). Moreover, despite the richness in terms of information of UKMED data, sample numbers for interview score are small, especially for those specifications with the largest number of covariates and as consequence that leads to less precise estimates. We had access to the Pilot UKMED dataset with doctors who started medical school in 2007 and 2008. The next UKMED release will include doctors from the 2007 cohort through 2014 and therefore a repetition of the analysis with a larger sample can improve the precision of the analysis and confirm the relations found in this paper.

Care should be taken not to conclude that the entire unexplained effect represents discrimination since it may be also driven by unobserved characteristics affecting interview scores. Nonetheless, our results suggest the necessity of a careful examination of the selection process to identify the elements driving the *unexplained* part of the differences in the interview score. This becomes especially important in a setting where doctors receive postgraduate specialty training funded by taxation and are subsequently employed by the National Health System, also funded by taxpayers. For that reason, it is important to ensure that taxpayer's contributions do not help the perpetuation of the observed unbalances.

3.6 Conclusion

In this chapter we have developed a conceptual framework and an empirical analysis of the sequential two-sided specialty allocation process in the UK. The focus has been on how doctors' socio-demographic characteristics affect their application decisions and the selectors' valuations of the candidates. The conceptual framework sets out the relevant elements of the process acknowledging that application decisions not only depend on the net benefit associated with each specialty but also on the perceived probability of getting access to each of them. The perceived probability determines the number of applications a doctor makes, and the latter affects the interview score, which is the key element from the selection stage.

The results from the empirical analysis show clear and significant effects that, after controlling for previous academic attainment, medical school effects and other relevant elements, doctors' demographic and socioeconomic backgrounds have a significant impact in determining their preferences in the application stage, the number of applications they submit and are also relevant in determining selectors' judgements.

These results contain information that policy makers can use to ensure that policies aim at addressing differential attainment in the specialty allocation process are correctly targeted. For instance, if the objective is to attract female doctors to surgical or highly remunerated specializations the policy actions need to be concentrated before (or during) the application stage. Examples of remedial actions can be the implementation of mentoring schemes or the introduction of visible female role models from the underrepresented specializations during medical studies and foundation training. Chapter 4 expands upon the effect of role models in determining specialty choices using data from Spanish doctors. In a survey of factors influencing careers choices, Lambert et al. (2016) found that domestic circumstances and work hours increased in importance from year one in medical school to year five more than any other factor. For that reason, making available information and case studies on how to reconcile work and domestic circumstances can be also an important remedial action to attract females to those fields.

Alternatively, if the objective is to improve BME doctors' attainment in the specialty allocation process, a policy action could be to provide more guidance on how to tackle the application stage. If making more applications in reality does imply producing lower quality applications, BME doctors should be encouraged to apply *wisely* and focus their efforts on one option. Moreover, the selection stage needs to be examined carefully to identify the elements that are driving the *unexplained* differences in interview scores. Those could be unobservable elements affecting interview outcomes (and correlated with the doctor's ethnicity) or information asymmetries leading to statistical discrimination problems.

Finally regarding socioeconomic background, we find that doctors from privileged backgrounds are more likely to apply to highly remunerated specialties and less likely to primary care specialties, that recurrently suffer from recruitment problems. Therefore, interventions designed to attract more doctors to primary care specialties should aim to make the medical workforce *less elitist* by ensuring a diversified intake of medical students.

Acknowledgements

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3.7 Tables

Table 3.1: List of variables in UKMED

Variable Name	Type	Description	Classification	Notes
		Demographic Variables (DE)		
Woman	Categorical	Equals 1 if individual is a woman; 0 otherwise	Demographic	
Age Process	Numerical	Doctor's age when starts the specialty allocation process	Demographic	
Time Elapsed	Numerical	Time elapsed between obtaining Primary Medical Qualification and participating in the specialty allocation process		
BME	Categorical	Equals 1 if doctor's ethnicity is Black and Minority Ethnic (BME) and 0 if the doctor is white	Demographic	
		Socioeconomic Variables (SE)		
Parent Doctor	Categorical	Equals 1 if the doctor's parent is a medical practitioner; 0 otherwise	Socioeconomic	
POLAR3	Categorical	Three categories: Low participation, Non-UK, Other (non-deprived) Neighbourhood	Socioeconomic	
School	Categorical	Three categories: State, Private and Unknown School	Socioeconomic	
		Academic Variables (AC)		
Graduate	Categorical	Equals 1 if doctor is graduate on entry (i.e. holds a BSc from another field); 0 otherwise	Academic	
Year Start	Categorical	Two categories: 2007 & 2008	Academic	
Medical School	Categorical	30 Medical Schools	Academic	
Top 5 Uni	Categorical	Equals 1 if doctor attended a top 5 medical school; 0 otherwise	Academic	Top 5 Medical Schools in the period 2013-2015 according to the Guardian Ranking: Cambridge, Oxford, Edimburgh, University College London and Dundee
Foundation School	Categorical	28 Foundation Schools	Academic	
UKCAT Score	Numerical	Score in the United Kingdom Clinical Aptitude Test (UKCAT)	Academic	
		Specialty Allocation Process Variables (OS)		
Year Process	Categorical	Four categories: 2012, 2013, 2014 & 2015	Application Stage	
Number Applications	Numerical	Total number of applications made by the student	Application Stage	
AppliMore	Categorical	Equals 1 if the doctor makes at least two application and 0 if only makes one	Application Stage	
RunThro	Categorical	Equals 1 if the doctor applies to a run-through specialty and 0 otherwise	Application Stage	See Table 3.2 for the list of specialties classified as *RunThro*
TopInc	Categorical	Equals 1 if the doctor applies to a top income specialty and 0 otherwise	Application Stage	Specialties with mean income above the 75^{Th} percentile of the income distribution (see Table 3.2)
BottomInc	Categorical	Equals 1 if the doctor applies to a bottom income specialty and 0 otherwise	Application Stage	Specialties with mean income below the 25^{Th} percentile of the income distribution (see Table 3.2)
PrimaryC	Categorical	Equals 1 if the doctor applies to a primary care specialty and 0 otherwise	Application Stage	See Table 3.2 for the list of specialties classified as *PrimaryC*
Surgical	Categorical	Equals 1 if the doctor applies to a surgical specialty and 0 otherwise	Application Stage	See Table 3.2 for the list of specialties classified as *Surgical*
Interview Score	Numerical	Interview score	Selection Stage	See Table 3.11
Shorlisting Score	Numerical	Shortlisting score	Selection Stage	

Table 3.2: List of specialties

Specialization (ST1/CT1)	Run-through	High-Income	Low-Income	Primary Care	Surgical	Total number of applications in UKMED	Total number of offers in UKMED
Acute Care Common Stem (ACCS)						442	319
Broad Based Training (BBT)						229	110
Cardio-thoracic surgery (CTS)	x	x			x	36	7
Clinical radiology (CR)	x					291	144
Community Sexual and Reproductive Health (CSRH)	x			x		25	3
Core Anaesthetics Training (CAT)						917	610
Core Medical Training (CMT)						2280	1663
Core Psychiatry Training (CPT)			x			404	314
Core Surgical Training (CST)		x			x	1056	687
General Practice (GP)	x			x		3306	2463
Histopathology (HP)	x					58	43
Neurosurgery (NS)	x	x			x	77	30
Obstetrics and Gynaecology (O&G)	x			x	x	367	219
Ophthalmology (OPH)	x	x			x	186	65
Paediatrics (PAE)	x		x	x		631	481
Public Health Medicine (PHM)	x		x			72	22

Table 3.3: Variables included in each Specification of the application stage analysis

Specification (1)	*Woman*, *BME*, *Age Process*,*Time Elapsed*, *Parent Doctor*, *POLAR3*, *School*, *Graduate*, *Top 5 Uni*, *Year Start* and *Year Process*
Specification (2)	(1) + *Medical School* and *Foundation School*
Specification (3)	(2) + *UKCAT Score*
Specification (1*)	Specification (2)
Specification (2*)	(1*) + *RunThro*
Specification (3*)	(1*) + *BottomInc*
Specification (4*)	(1*) + *PrimaryC*
Specification (5*)	(1*) + *Surgical*
Specification (6*)	(1*) + *TopInc*

Specifications marked with an asterisk only apply to the dependent variable *AppliMore*

Table 3.4: Descriptive statistics: application stage

	Sample 1 - All doctors					Sample 2 - Single application					UKMED Population				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Gender: Men	7,630	0.419	0.49	0	1	5,387	0.420	0.49	0	1	13,745	0.429	0.49	0	1
Gender: Women	7,630	0.581	0.49	0	1	5,387	0.580	0.49	0	1	13,745	0.571	0.49	0	1
Age Process	7,630	27.69	3.41	24	54	5,387	27.61	3.32	24	54	7,630	27.69	3.41	24	54
Age PMQ	7,630	25.60	3.39	22	52	5,387	25.51	3.30	22	52	13,745	25.32	2.97	22	52
Time Elapsed	7,630	2.089	0.29	2	4	5,387	2.095	0.30	2	4	7,630	2.089	0.29	2	4
Ethnicity: White	7,591	0.678	0.47	0	1	5,365	0.701	0.46	0	1	13,683	0.694	0.46	0	1
Ethnicity: BME	7,591	0.322	0.47	0	1	5,365	0.299	0.46	0	1	13,683	0.306	0.46	0	1
POLAR3: Low participation Neighbourhood	7,592	0.041	0.20	0	1	5,357	0.042	0.20	0	1	13,659	0.038	0.19	0	1
POLAR3: Non-UK Neighbourhood	7,592	0.098	0.30	0	1	5,357	0.077	0.27	0	1	13,659	0.086	0.28	0	1
POLAR3: Other Neighbourhood	7,592	0.861	0.35	0	1	5,357	0.881	0.32	0	1	13,659	0.876	0.33	0	1
School: State	7,630	0.639	0.48	0	1	5,387	0.648	0.48	0	1	13,745	0.632	0.48	0	1
School: Private	7,630	0.213	0.41	0	1	5,387	0.223	0.42	0	1	13,745	0.244	0.43	0	1
School:Unknown	7,630	0.148	0.36	0	1	5,387	0.129	0.34	0	1	13,745	0.124	0.33	0	1
Parent Doctor	7,630	0.113	0.32	0	1	5,387	0.120	0.32	0	1	13,745	0.127	0.33	0	1
Year Process: 2012	7,630	0.008	0.09	0	1	5,387	0.006	0.08	0	1	7,630	0.008	0.09	0	1
Year Process: 2013	7,630	0.074	0.26	0	1	5,387	0.074	0.26	0	1	7,630	0.074	0.26	0	1
Year Process: 2014	7,630	0.352	0.48	0	1	5,387	0.348	0.48	0	1	7,630	0.352	0.48	0	1
Year Process: 2015	7,630	0.566	0.50	0	1	5,387	0.572	0.49	0	1	7,630	0.566	0.50	0	1
Year Medical School: 2007	7,630	0.666	0.47	0	1	5,387	0.671	0.47	0	1	13,745	0.507	0.50	0	1
Year Medical School: 2008	7,630	0.334	0.47	0	1	5,387	0.329	0.47	0	1	13,745	0.493	0.50	0	1
Graduate: Yes	7,630	0.266	0.44	0	1	5,387	0.259	0.44	0	1	13,745	0.183	0.39	0	1
Graduate: No	7,630	0.734	0.44	0	1	5,387	0.741	0.44	0	1	13,745	0.817	0.39	0	1
UKCAT score	6,485	25.08	2.23	16.3	33.4	4,609	25.13	2.23	16.3	33.4	12,096	25.24	2.20	16.3	33.4
Top 5 Uni	7,630	0.123	0.33	0	1	5,387	0.12	0.33	0	1	13,765	0.135	0.34	0	1
AppliMore	7,630	0.294	0.46	0	1	-	-	-	-	-					
RunThrou	7,630	0.589	0.49	0	1	5,387	0.503	0.50	0	1					
TopInc	7,630	0.109	0.31	0	1	5,387	0.134	0.34	0	1					
BottomInc	7,630	0.143	0.35	0	1	5,387	0.101	0.30	0	1					
PrimaryC	7,630	0.530	0.50	0	1	5,387	0.459	0.50	0	1					
Surgical	7,630	0.204	0.40	0	1	5,387	0.171	0.38	0	1					
Women*AppliMore	7,630	0.172	0.38	0	1										
Women*RunThrou	7,630	0.377	0.48	0	1	5,387	0.332	0.47	0	1					
Women*TopInc	7,630	0.039	0.19	0	1	5,387	0.048	0.21	0	1					
Women*BottomInc	7,630	0.096	0.30	0	1	5,387	0.069	0.25	0	1					
Women*PrimaryC	7,630	0.352	0.48	0	1	5,387	0.311	0.46	0	1					
Women*Surgical	7,630	0.099	0.30	0	1	5,387	0.081	0.27	0	1					
BME*AppliMore	7,591	0.111	0.31	0	1	-	-	-	-						
BME*RunThrou	7,591	0.202	0.40	0	1	5,365	0.154	0.36	0	1					
BME*TopInc	7,591	0.043	0.20	0	1	5,365	0.051	0.22	0	1					
BME*BottomInc	7,591	0.041	0.20	0	1	5,365	0.022	0.15	0	1					
BME*PrimaryC	7,591	0.174	0.38	0	1	5,365	0.137	0.34	0	1					
BME*Surgical	7,591	0.085	0.28	0	1	5,365	0.062	0.24	0	1					

Table 3.5: Probit estimation results variable $RunThro$

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Woman	0.393***	0.148***	0.397***	0.148***	0.397***	0.148***	0.439***	0.169***	0.445***	0.168***	0.450***	0.169***
	(0.030)		(0.030)		(0.033)		(0.036)		(0.036)		(0.039)	
Age Process	0.029***	0.011***	0.028***	0.010***	0.033***	0.012***	0.032***	0.012***	0.031***	0.012***	0.039***	0.015***
	(0.006)		(0.006)		(0.008)		(0.007)		(0.007)		(0.009)	
Time Elapsed	-0.015	-0.006	-0.044	-0.016	-0.025	-0.009	0.032	0.012	-0.020	-0.007	0.012	0.005
	(0.054)		(0.056)		(0.064)		(0.062)		(0.066)		(0.076)	
BME	0.247***	0.093***	0.226***	0.084***	0.218***	0.081***	0.166***	0.064***	0.149***	0.056***	0.161***	0.060***
	(0.034)		(0.036)		(0.040)		(0.040)		(0.043)		(0.047)	
Parent Doctor	-0.108**	-0.041**	-0.103**	-0.038**	-0.087*	-0.033*	-0.113**	-0.043**	-0.108*	-0.041*	-0.102*	-0.038*
	(0.048)		(0.048)		(0.051)		(0.055)		(0.056)		(0.059)	
POLAR3: Low participation	-0.070	-0.026	-0.069	-0.026	-0.080	-0.030	-0.055	-0.021	-0.060	-0.023	-0.049	-0.018
	(0.074)		(0.075)		(0.083)		(0.087)		(0.089)		(0.097)	
POLAR3: Non-UK	-0.167**	-0.064**	-0.159**	-0.060**	-0.122	-0.046	-0.412***	-0.156***	-0.410***	-0.153***	-0.393***	-0.146***
	(0.070)		(0.071)		(0.083)		(0.091)		(0.093)		(0.108)	
School: Independent	-0.045	-0.017	-0.015	-0.006	-0.021	-0.008	-0.054	-0.021	-0.029	-0.011	-0.039	-0.015
	(0.038)		(0.039)		(0.041)		(0.044)		(0.045)		(0.048)	
School:Unknown	-0.033	-0.012	-0.018	-0.007	-0.039	-0.014	-0.055	-0.021	-0.046	-0.017	-0.055	-0.021
	(0.059)		(0.060)		(0.070)		(0.072)		(0.073)		(0.086)	
Graduate	-0.025	-0.010	0.010	0.004	-0.034	-0.013	-0.072	-0.027	-0.009	-0.004	-0.081	-0.030
	(0.051)		(0.055)		(0.063)		(0.060)		(0.065)		(0.077)	
Year Process: 2012	-0.067	-0.026	-0.169	-0.064	-1.308**	-0.430**	-0.160	-0.061	-0.314	-0.117	-1.132	-0.351
	(0.186)		(0.188)		(0.665)		(0.255)		(0.255)		(0.748)	
Year Process: 2013	0.223***	0.083***	0.165**	0.061**	0.116	0.043	0.248***	0.095***	0.171*	0.065*	0.115	0.043
	(0.072)		(0.078)		(0.108)		(0.086)		(0.093)		(0.125)	
Year Process: 2014	0.104***	0.040***	0.067*	0.025*	0.093**	0.035**	0.139***	0.054***	0.084*	0.032*	0.109**	0.041**
	(0.037)		(0.040)		(0.044)		(0.044)		(0.047)		(0.052)	
Year Medical School: 2008	0.034	0.013	-0.008	-0.003	0.029	0.011	0.053	0.020	0.001	0.000	0.034	0.013
	(0.036)		(0.039)		(0.044)		(0.043)		(0.046)		(0.052)	
Top5 Uni	-0.126***	-0.047***					-0.130**	-0.050**				
	(0.045)						(0.054)					
UKCAT Score					-0.034***	-0.013***					-0.035***	-0.013***
					(0.008)						(0.010)	
Aberdeen			0.179	0.067	0.038	0.014			0.160	0.061	0.009	0.004
			(0.138)		(0.146)				(0.158)		(0.168)	
Barts			0.175*	0.066*	0.193*	0.072*			0.207*	0.079*	0.234*	0.088*
			(0.102)		(0.109)				(0.123)		(0.132)	
Birmingham			0.000	0.000	0.000	0.000			0.000	0.000	0.000	0.000
			(.)		(.)				(.)		(.)	
Brighton and Sussex			0.040	0.015	0.034	0.013			0.045	0.017	0.024	0.009
			(0.132)		(0.139)				(0.154)		(0.163)	
Bristol			0.049	0.019	0.054	0.021			0.092	0.035	0.076	0.029
			(0.119)		(0.133)				(0.138)		(0.155)	
Cambridge			-0.019	-0.007	0.077	0.029			0.028	0.011	0.148	0.056
			(0.139)		(0.154)				(0.168)		(0.185)	
Cardiff			0.101	0.038	0.089	0.033			0.144	0.055	0.132	0.050
			(0.107)		(0.126)				(0.128)		(0.150)	
Dundee			0.070	0.026	-0.045	-0.017			0.066	0.025	-0.080	-0.030
			(0.147)		(0.154)				(0.178)		(0.186)	
Edinburgh			-0.134	-0.051	-0.127	-0.049			-0.160	-0.060	-0.155	-0.058
			(0.131)		(0.140)				(0.158)		(0.168)	

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Table 3.5 – continued from previous page

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Glasgow			-0.017	-0.006	-0.064	-0.025			-0.101	-0.038	-0.174	-0.065
			(0.130)		(0.141)				(0.158)		(0.171)	
Hull York			0.317**	0.117**	0.323**	0.118**			0.305*	0.116*	0.308*	0.116*
			(0.133)		(0.140)				(0.162)		(0.171)	
Imperial			0.012	0.004	0.058	0.022			-0.075	-0.028	0.000	0.000
			(0.112)		(0.121)				(0.138)		(0.149)	
Keele			-0.037	-0.014	-0.064	-0.025			0.049	0.019	0.011	0.004
			(0.122)		(0.128)				(0.146)		(0.153)	
King's			-0.010	-0.004	0.000	0.000			-0.045	-0.017	-0.011	-0.004
			(0.108)		(0.118)				(0.129)		(0.141)	
Lancaster			0.008	0.003	-0.037	-0.014			0.014	0.005	-0.063	-0.024
			(0.189)		(0.210)				(0.214)		(0.240)	
Leeds			0.107	0.040	0.105	0.040			0.143	0.054	0.166	0.063
			(0.127)		(0.138)				(0.152)		(0.166)	
Leicester			0.274**	0.102**	0.246**	0.091**			0.235*	0.089*	0.203	0.076
			(0.109)		(0.116)				(0.130)		(0.138)	
Liverpool			0.202*	0.075*	0.137	0.051			0.164	0.062	0.106	0.040
			(0.112)		(0.122)				(0.133)		(0.145)	
Manchester			0.220**	0.082**	0.248**	0.092**			0.298**	0.113**	0.325**	0.122**
			(0.106)		(0.114)				(0.127)		(0.137)	
Newcastle			0.254**	0.094**	0.293**	0.108**			0.239*	0.091*	0.271*	0.102*
			(0.117)		(0.124)				(0.140)		(0.149)	
Norwich			0.037	0.014	0.013	0.005			0.090	0.034	0.072	0.027
			(0.118)		(0.125)				(0.143)		(0.153)	
Nottingham			0.092	0.035	0.094	0.035			0.192	0.073	0.190	0.072
			(0.102)		(0.113)				(0.118)		(0.130)	
Oxford			-0.038	-0.015	0.129	0.049			-0.300	-0.110	-0.122	-0.046
			(0.140)		(0.150)				(0.182)		(0.193)	
Peninsula			0.234*	0.087*	0.268**	0.099**			0.328**	0.124**	0.329**	0.123**
			(0.122)		(0.134)				(0.143)		(0.156)	
Queen's			0.140	0.053	0.029	0.011			0.206	0.078	0.168	0.063
			(0.165)		(0.182)				(0.207)		(0.225)	
Sheffield			0.204	0.076	0.182	0.068			0.254	0.096	0.283*	0.107*
			(0.133)		(0.143)				(0.156)		(0.168)	
Southampton			0.120	0.045	0.068	0.026			0.124	0.047	0.066	0.025
			(0.109)		(0.119)				(0.131)		(0.142)	
St George's			0.103	0.039	0.042	0.016			0.149	0.057	0.074	0.028
			(0.106)		(0.120)				(0.124)		(0.142)	
UCL			-0.054	-0.021	-0.014	-0.005			-0.069	-0.026	-0.052	-0.019
			(0.117)		(0.129)				(0.140)		(0.154)	
Warwick			0.151	0.057	0.082	0.031			0.121	0.046	0.057	0.021
			(0.119)		(0.136)				(0.143)		(0.163)	
N	7,553		7,553		6,441		5,335		5,335		4,576	
Foundation School	NO		YES		YES		NO		YES		YES	
R^2	0.028		0.038		0.042		0.034		0.049		0.053	
Log-likelihood	-4972.881		-4921.312		-4186.153		-3570.768		-3516.249		-3003.024	
$Pr(y=1)$	0.588		0.588		0.586		0.501		0.501		0.502	

[a] Base outcomes: Gender: Men, Ethnicity: White, School: State, POLAR3:Other neighbourhood, Year Medical School: 2007, Year Process: 2015, Medical School: Birmingham, Foundation School: Birmingham

[b] SE: Standard Errors; AME: Average Marginal Effect

[c] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.6: Probit estimation results variable $TopInc$

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Woman	-0.525***	-0.094***	-0.538***	-0.094***	-0.545***	-0.094***	-0.543***	-0.112***	-0.560***	-0.112***	-0.584***	-0.115***
	(0.040)		(0.040)		(0.044)		(0.045)		(0.046)		(0.050)	
Age Process	-0.017**	-0.003**	-0.019**	-0.003**	-0.023**	-0.004**	-0.016*	-0.003*	-0.015*	-0.003*	-0.024**	-0.005**
	(0.007)		(0.008)		(0.010)		(0.009)		(0.009)		(0.011)	
Time Elapsed	-0.222***	-0.040***	-0.200**	-0.035**	-0.222**	-0.038**	-0.168*	-0.035*	-0.144	-0.029	-0.133	-0.026
	(0.082)		(0.085)		(0.096)		(0.087)		(0.091)		(0.104)	
BME	0.108**	0.019**	0.145***	0.025***	0.161***	0.028***	0.145***	0.030***	0.180***	0.036***	0.201***	0.040***
	(0.044)		(0.048)		(0.052)		(0.049)		(0.054)		(0.058)	
Parent Doctor	0.156***	0.028***	0.145**	0.025**	0.135**	0.023**	0.153**	0.031**	0.151**	0.030**	0.135*	0.027*
	(0.060)		(0.061)		(0.064)		(0.066)		(0.067)		(0.072)	
POLAR3: Low participation	0.000	0.000	0.034	0.006	0.008	0.001	-0.072	-0.014	-0.033	-0.007	-0.024	-0.005
	(0.101)		(0.102)		(0.114)		(0.117)		(0.118)		(0.130)	
POLAR3: Non-UK	0.137	0.026	0.112	0.021	0.137	0.025	0.209*	0.047*	0.172	0.037	0.244*	0.054*
	(0.090)		(0.092)		(0.103)		(0.109)		(0.112)		(0.125)	
School: Independent	0.113**	0.021**	0.076	0.014	0.091*	0.016*	0.142***	0.030***	0.110**	0.022**	0.133**	0.027**
	(0.049)		(0.050)		(0.053)		(0.054)		(0.056)		(0.059)	
School:Unknown	0.097	0.017	0.089	0.016	0.071	0.012	0.107	0.022	0.110	0.023	0.100	0.020
	(0.076)		(0.077)		(0.091)		(0.091)		(0.092)		(0.107)	
Graduate	0.126*	0.023*	0.128*	0.023*	0.172**	0.031**	0.099	0.021	0.101	0.021	0.143	0.029
	(0.069)		(0.074)		(0.085)		(0.077)		(0.083)		(0.098)	
Year Process: 2012	0.024	0.005	0.047	0.009	0.728	0.182	0.132	0.030	0.130	0.028	1.194*	0.361*
	(0.231)		(0.236)		(0.769)		(0.283)		(0.292)		(0.713)	
Year Process: 2013	-0.096	-0.017	-0.054	-0.009	0.101	0.019	-0.072	-0.014	-0.048	-0.009	0.157	0.033
	(0.096)		(0.104)		(0.139)		(0.109)		(0.119)		(0.156)	
Year Process: 2014	-0.062	-0.011	-0.019	-0.003	-0.046	-0.008	-0.029	-0.006	0.011	0.002	0.001	0.000
	(0.049)		(0.053)		(0.059)		(0.056)		(0.061)		(0.067)	
Year Medical School: 2008	-0.114**	-0.020**	-0.073	-0.013	-0.047	-0.008	-0.066	-0.013	-0.024	-0.005	0.029	0.006
	(0.049)		(0.052)		(0.059)		(0.055)		(0.059)		(0.066)	
Top5 Uni	-0.001	-0.000					-0.045	-0.009				
	(0.060)						(0.069)					
UKCAT Score					-0.006	-0.001					-0.009	-0.002
					(0.011)						(0.012)	
Aberdeen			0.070	0.015	0.163	0.035			-0.026	-0.006	0.085	0.021
			(0.185)		(0.194)				(0.202)		(0.211)	
Barts			-0.306**	-0.053**	-0.305**	-0.051**			-0.433***	-0.088***	-0.445***	-0.086***
			(0.141)		(0.150)				(0.160)		(0.170)	
Brighton and Sussex			-0.229	-0.042	-0.149	-0.027			-0.370*	-0.078*	-0.263	-0.056
			(0.188)		(0.195)				(0.211)		(0.221)	
Bristol			-0.106	-0.021	-0.158	-0.029			-0.160	-0.037	-0.195	-0.043
			(0.157)		(0.180)				(0.171)		(0.196)	
Cambridge			0.053	0.011	0.133	0.028			-0.325	-0.070	-0.278	-0.058
			(0.173)		(0.191)				(0.206)		(0.228)	
Cardiff			-0.130	-0.025	-0.268	-0.046			-0.153	-0.036	-0.288	-0.060
			(0.142)		(0.168)				(0.157)		(0.185)	
Dundee			-0.138	-0.026	-0.059	-0.011			-0.247	-0.055	-0.124	-0.028
			(0.210)		(0.222)				(0.244)		(0.254)	
Edinburgh			-0.008	-0.002	0.068	0.014			-0.046	-0.011	0.022	0.005
			(0.162)		(0.174)				(0.184)		(0.196)	
Glasgow			-0.067	-0.013	0.063	0.013			-0.081	-0.019	0.043	0.010
			(0.174)		(0.186)				(0.199)		(0.212)	

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Table 3.6 – continued from previous page

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Hull York			-0.495**	-0.077**	-0.405**	-0.064**			-0.741***	-0.128***	-0.648***	-0.112***
			(0.192)		(0.199)				(0.222)		(0.229)	
Imperial			-0.104	-0.020	-0.070	-0.013			-0.091	-0.022	-0.074	-0.017
			(0.145)		(0.157)				(0.164)		(0.178)	
Keele			-0.012	-0.002	-0.016	-0.003			-0.099	-0.024	-0.070	-0.016
			(0.162)		(0.172)				(0.180)		(0.190)	
King's			-0.098	-0.019	-0.095	-0.018			-0.214	-0.048	-0.188	-0.041
			(0.140)		(0.154)				(0.160)		(0.174)	
Lancaster			-0.169	-0.032	-0.343	-0.056			-0.220	-0.050	-0.378	-0.075
			(0.264)		(0.304)				(0.278)		(0.321)	
Leeds			0.007	0.001	0.035	0.007			-0.074	-0.018	-0.074	-0.017
			(0.168)		(0.186)				(0.196)		(0.218)	
Leicester			-0.258*	-0.046*	-0.308*	-0.051*			-0.294*	-0.064*	-0.357*	-0.072*
			(0.156)		(0.168)				(0.177)		(0.190)	
Liverpool			-0.284*	-0.050*	-0.179	-0.032			-0.320*	-0.069*	-0.243	-0.052
			(0.155)		(0.168)				(0.172)		(0.185)	
Manchester			0.034	0.007	0.074	0.015			0.054	0.014	0.101	0.025
			(0.139)		(0.149)				(0.155)		(0.166)	
Newcastle			-0.205	-0.038	-0.181	-0.032			-0.266	-0.059	-0.225	-0.048
			(0.159)		(0.169)				(0.179)		(0.192)	
Norwich			-0.438**	-0.071**	-0.517***	-0.076***			-0.717***	-0.126***	-0.743***	-0.122***
			(0.181)		(0.198)				(0.230)		(0.241)	
Nottingham			0.041	0.009	0.084	0.017			-0.076	-0.018	-0.052	-0.012
			(0.136)		(0.150)				(0.150)		(0.165)	
Oxford			-0.456**	-0.073**	-0.465**	-0.070**			-0.542**	-0.104**	-0.509**	-0.095**
			(0.196)		(0.212)				(0.234)		(0.250)	
Peninsula			-0.290*	-0.051*	-0.239	-0.041			-0.375**	-0.078**	-0.326*	-0.067*
			(0.160)		(0.172)				(0.178)		(0.191)	
Queen's			-0.097	-0.019	0.072	0.015			-0.177	-0.041	-0.031	-0.007
			(0.252)		(0.285)				(0.289)		(0.327)	
Sheffield			-0.368*	-0.062*	-0.344	-0.056			-0.442**	-0.089**	-0.423*	-0.083*
			(0.192)		(0.213)				(0.210)		(0.234)	
Southampton			-0.055	-0.011	-0.068	-0.013			-0.165	-0.038	-0.179	-0.039
			(0.146)		(0.160)				(0.166)		(0.182)	
St George's			-0.238	-0.043	-0.150	-0.027			-0.323**	-0.069**	-0.213	-0.046
			(0.146)		(0.165)				(0.160)		(0.181)	
UCL			-0.117	-0.023	-0.107	-0.020			-0.249	-0.055	-0.177	-0.039
			(0.150)		(0.164)				(0.170)		(0.183)	
Warwick			-0.415**	-0.068**	-0.419**	-0.065**			-0.533***	-0.103***	-0.568**	-0.103**
			(0.168)		(0.194)				(0.197)		(0.226)	
Constant	-0.123		-0.285		0.021		-0.167		-0.382		0.032	
	(0.277)		(0.318)		(0.450)		(0.307)		(0.352)		(0.504)	
N	7,553		7,553		6,441		5,335		5,335		4,576	
Foundation School	NO		YES		YES		NO		YES		YES	
R^2	0.047		0.064		0.068		0.051		0.071		0.078	
Log-likelihood	-2476.845		-2431.321		-2046.046		-1995.104		-1951.593		-1648.056	
$Pr(y=1)$	0.109		0.109		0.107		0.136		0.135		0.133	

[a] Base outcomes: Gender: Man, Ethnicity:White, School: State, POLAR3:Other neighbourhood, Year Medical School: 2007, Year Process: 2015, Medical School: Birmingham, Foundation School: Birmingham

[b] SE: Standard Errors; AME: Average Marginal Effect

[c] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.7: Probit estimation results variable $BottomInc$

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Woman	0.234***	0.052***	0.241***	0.053***	0.245***	0.053***	0.238***	0.042***	0.236***	0.041***	0.252***	0.042***
	(0.037)		(0.038)		(0.041)		(0.050)		(0.050)		(0.054)	
Age Process	0.000	0.000	-0.001	-0.000	0.001	0.000	-0.013	-0.002	-0.014	-0.002	-0.012	-0.002
	(0.007)		(0.007)		(0.008)		(0.010)		(0.010)		(0.013)	
Time Elapsed	0.122*	0.027*	0.129*	0.028*	0.143*	0.031*	0.153**	0.027**	0.139*	0.024*	0.143	0.024
	(0.063)		(0.066)		(0.076)		(0.078)		(0.083)		(0.095)	
BME	-0.094**	-0.021**	-0.140***	-0.031***	-0.140***	-0.030***	-0.217***	-0.038***	-0.271***	-0.047***	-0.257***	-0.043***
	(0.041)		(0.044)		(0.049)		(0.056)		(0.060)		(0.065)	
Parent Doctor	-0.087	-0.019	-0.086	-0.019	-0.087	-0.019	-0.092	-0.016	-0.088	-0.015	-0.114	-0.019
	(0.061)		(0.061)		(0.065)		(0.078)		(0.079)		(0.084)	
POLAR3: Low participation	-0.055	-0.012	-0.045	-0.010	-0.027	-0.006	0.027	0.005	0.046	0.008	0.097	0.017
	(0.093)		(0.094)		(0.104)		(0.118)		(0.119)		(0.130)	
POLAR3: Non-UK	0.035	0.008	0.053	0.012	0.030	0.006	-0.033	-0.006	-0.003	-0.001	0.017	0.003
	(0.081)		(0.081)		(0.096)		(0.121)		(0.124)		(0.146)	
School: Independent	0.029	0.006	0.023	0.005	0.004	0.001	0.029	0.005	0.018	0.003	-0.008	-0.001
	(0.047)		(0.048)		(0.051)		(0.060)		(0.061)		(0.065)	
School:Unknown	0.115*	0.026*	0.122*	0.028*	0.140*	0.032*	0.084	0.015	0.076	0.014	0.081	0.014
	(0.067)		(0.068)		(0.082)		(0.094)		(0.096)		(0.117)	
Graduate	0.061	0.014	0.031	0.007	0.010	0.002	0.069	0.012	0.083	0.015	-0.001	-0.000
	(0.060)		(0.063)		(0.074)		(0.080)		(0.086)		(0.101)	
Year Process: 2012	0.030	0.007	0.060	0.014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.219)		(0.222)		(.)		(.)		(.)		(.)	
Year Process: 2013	0.041	0.010	0.028	0.006	-0.203	-0.041	-0.024	-0.004	-0.072	-0.013	-0.168	-0.027
	(0.083)		(0.090)		(0.129)		(0.110)		(0.120)		(0.169)	
Year Process: 2014	-0.065	-0.014	-0.062	-0.014	-0.078	-0.017	-0.141**	-0.024**	-0.142**	-0.024**	-0.173**	-0.028**
	(0.046)		(0.049)		(0.054)		(0.061)		(0.065)		(0.074)	
Year Medical School: 2008	0.006	0.001	0.008	0.002	-0.027	-0.006	-0.049	-0.009	-0.055	-0.010	-0.073	-0.012
	(0.044)		(0.047)		(0.054)		(0.058)		(0.062)		(0.071)	
Top5 Uni	0.077	0.017					0.090	0.016				
	(0.054)						(0.070)					
UKCAT Score					0.030***	0.006***					0.033***	0.006***
					(0.010)						(0.013)	
Aberdeen			-0.226	-0.047	-0.256	-0.053			-0.428*	-0.061*	-0.387	-0.056
			(0.167)		(0.182)				(0.230)		(0.247)	
Barts			-0.075	-0.017	-0.028	-0.007			-0.131	-0.023	-0.079	-0.014
			(0.126)		(0.134)				(0.166)		(0.180)	
Brighton and Sussex			-0.026	-0.006	-0.013	-0.003			-0.093	-0.016	-0.034	-0.006
			(0.160)		(0.168)				(0.210)		(0.222)	
Bristol			-0.060	-0.014	-0.119	-0.026			0.062	0.012	-0.012	-0.002
			(0.141)		(0.161)				(0.171)		(0.201)	
Cambridge			0.202	0.052	0.046	0.011			0.170	0.035	0.037	0.007
			(0.161)		(0.184)				(0.205)		(0.236)	
Cardiff			-0.076	-0.017	-0.132	-0.029			-0.086	-0.015	-0.181	-0.030
			(0.131)		(0.158)				(0.163)		(0.200)	
Dundee			-0.202	-0.043	-0.249	-0.052			-0.143	-0.025	-0.168	-0.028
			(0.176)		(0.188)				(0.230)		(0.244)	
Edinburgh			-0.191	-0.041	-0.326*	-0.065*			-0.199	-0.033	-0.288	-0.044
			(0.162)		(0.175)				(0.209)		(0.224)	
Glasgow			-0.038	-0.009	-0.104	-0.023			-0.315	-0.048	-0.368	-0.054
			(0.157)		(0.168)				(0.213)		(0.229)	

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Table 3.7 – continued from previous page

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Hull York			0.025	0.006	0.024	0.006			-0.345	-0.052	-0.374	-0.054
			(0.156)		(0.165)				(0.244)		(0.267)	
Imperial			-0.132	-0.029	-0.213	-0.045			-0.153	-0.026	-0.222	-0.036
			(0.144)		(0.158)				(0.191)		(0.211)	
Keele			-0.019	-0.004	0.017	0.004			0.016	0.003	0.059	0.011
			(0.146)		(0.153)				(0.182)		(0.193)	
King's			0.118	0.029	0.035	0.008			0.033	0.006	0.018	0.003
			(0.128)		(0.143)				(0.169)		(0.189)	
Lancaster			-0.135	-0.030	-0.072	-0.016			-0.092	-0.016	-0.022	-0.004
			(0.236)		(0.262)				(0.274)		(0.312)	
Leeds			-0.191	-0.041	-0.135	-0.030			-0.016	-0.003	0.104	0.020
			(0.161)		(0.176)				(0.204)		(0.224)	
Leicester			-0.021	-0.005	0.049	0.012			-0.004	-0.001	0.093	0.018
			(0.129)		(0.137)				(0.172)		(0.184)	
Liverpool			-0.059	-0.014	-0.101	-0.023			-0.108	-0.019	-0.073	-0.013
			(0.135)		(0.148)				(0.175)		(0.191)	
Manchester			-0.193	-0.041	-0.217	-0.046			-0.145	-0.025	-0.146	-0.024
			(0.131)		(0.143)				(0.161)		(0.178)	
Newcastle			-0.152	-0.033	-0.192	-0.041			-0.061	-0.011	-0.157	-0.026
			(0.140)		(0.153)				(0.168)		(0.185)	
Norwich			-0.185	-0.039	-0.199	-0.042			-0.246	-0.040	-0.222	-0.035
			(0.146)		(0.156)				(0.198)		(0.213)	
Nottingham			0.020	0.005	0.002	0.000			0.046	0.009	0.063	0.012
			(0.118)		(0.130)				(0.142)		(0.158)	
Oxford			0.094	0.023	0.115	0.029			0.042	0.008	0.056	0.011
			(0.164)		(0.172)				(0.221)		(0.232)	
Peninsula			-0.399**	-0.076**	-0.422**	-0.079**			-0.414**	-0.060**	-0.453*	-0.063*
			(0.165)		(0.189)				(0.204)		(0.239)	
Queen's			-0.218	-0.046	-0.389	-0.075			0.278	0.061	0.135	0.027
			(0.213)		(0.240)				(0.272)		(0.303)	
Sheffield			-0.055	-0.013	-0.040	-0.009			-0.023	-0.004	-0.005	-0.001
			(0.167)		(0.177)				(0.214)		(0.231)	
Southampton			-0.036	-0.008	-0.068	-0.015			-0.039	-0.007	-0.069	-0.012
			(0.133)		(0.148)				(0.173)		(0.193)	
St George's			0.130	0.032	0.052	0.013			0.135	0.027	-0.009	-0.002
			(0.123)		(0.143)				(0.154)		(0.188)	
UCL			0.126	0.031	0.135	0.034			0.229	0.049	0.246	0.052
			(0.139)		(0.152)				(0.171)		(0.190)	
Warwick			0.022	0.005	0.119	0.030			-0.120	-0.021	0.123	0.024
			(0.144)		(0.162)				(0.198)		(0.217)	
Constant	-1.464***		-1.171***		-2.033***		-1.301***		-1.042***		-1.966***	
	(0.230)		(0.255)		(0.388)		(0.320)		(0.344)		(0.517)	
N	7,553		7,553		6,437		5,305		5,305		4,573	
Foundation School	NO		YES		YES		NO		YES		YES	
R^2	0.012		0.021		0.023		0.018		0.032		0.038	
Log-likelihood	-3059.525		-3031.330		-2518.563		-1711.943		-1687.212		-1409.927	
$Pr(y=1)$	0.143		0.143		0.138		0.101		0.100		0.096	

[a] Base outcomes: Gender: Men, Ethnicity:White, School: State, POLAR3:Other neighbourhood, Year Medical School: 2007, Year Process: 2015, Medical School: Birmingham, Foundation School: Birmingham

[b] SE: Standard Errors; AME: Average Marginal Effect

[c] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.8: Probit estimation results variable $Surgical$

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Woman	-0.259***	-0.071***	-0.259***	-0.070***	-0.267***	-0.072***	-0.280***	-0.069***	-0.292***	-0.071***	-0.306***	-0.074***
	(0.033)		(0.034)		(0.037)		(0.041)		(0.042)		(0.046)	
Age Process	-0.009	-0.002	-0.010	-0.003	-0.016**	-0.004**	-0.017**	-0.004**	-0.018**	-0.004**	-0.029***	-0.007***
	(0.006)		(0.006)		(0.008)		(0.008)		(0.008)		(0.010)	
Time Elapsed	-0.246***	-0.068***	-0.219***	-0.059***	-0.192**	-0.052**	-0.172**	-0.043**	-0.141*	-0.034*	-0.149	-0.036
	(0.067)		(0.069)		(0.078)		(0.080)		(0.085)		(0.096)	
BME	0.216***	0.059***	0.233***	0.063***	0.217***	0.059***	0.097**	0.024**	0.131***	0.032***	0.140***	0.034***
	(0.037)		(0.040)		(0.043)		(0.046)		(0.050)		(0.054)	
Parent Doctor	0.126**	0.035**	0.119**	0.032**	0.098*	0.026*	0.145**	0.036**	0.136**	0.033**	0.116*	0.028*
	(0.053)		(0.053)		(0.056)		(0.063)		(0.063)		(0.067)	
POLAR3: Low participation	0.028	0.008	0.052	0.014	0.064	0.017	0.017	0.004	0.057	0.014	0.087	0.021
	(0.085)		(0.086)		(0.095)		(0.105)		(0.106)		(0.115)	
POLAR3: Non-UK	0.275***	0.082***	0.257***	0.075***	0.338***	0.101***	0.228**	0.062**	0.197*	0.052*	0.271**	0.072**
	(0.076)		(0.077)		(0.089)		(0.101)		(0.103)		(0.117)	
School: Independent	0.055	0.015	0.035	0.009	0.052	0.014	0.145***	0.037***	0.116**	0.029**	0.143***	0.035***
	(0.042)		(0.043)		(0.045)		(0.051)		(0.052)		(0.055)	
School:Unknown	0.077	0.021	0.077	0.021	0.043	0.012	0.137	0.035	0.133	0.033	0.111	0.027
	(0.065)		(0.066)		(0.079)		(0.084)		(0.085)		(0.100)	
Graduate	0.093*	0.026*	0.093	0.026	0.128*	0.035*	0.056	0.014	0.060	0.015	0.149	0.037
	(0.056)		(0.060)		(0.070)		(0.072)		(0.078)		(0.092)	
Year Process: 2012	0.039	0.011	0.059	0.017	0.948	0.332	0.245	0.069	0.244	0.067	0.830	0.269
	(0.195)		(0.203)		(0.610)		(0.254)		(0.267)		(0.716)	
Year Process: 2013	-0.071	-0.020	-0.032	-0.009	0.048	0.014	-0.049	-0.012	-0.020	-0.005	0.047	0.012
	(0.079)		(0.086)		(0.117)		(0.102)		(0.111)		(0.147)	
Year Process: 2014	-0.109***	-0.030***	-0.079*	-0.021*	-0.098**	-0.026**	-0.064	-0.016	-0.037	-0.009	-0.071	-0.017
	(0.041)		(0.044)		(0.049)		(0.052)		(0.056)		(0.062)	
Year Medical School: 2008	-0.118***	-0.033***	-0.083*	-0.022*	-0.071	-0.019	-0.060	-0.015	-0.019	-0.005	0.006	0.001
	(0.041)		(0.043)		(0.049)		(0.051)		(0.055)		(0.062)	
Top5 Uni	-0.033	-0.009					-0.016	-0.004				
	(0.051)						(0.063)					
UKCAT Score					-0.016*	-0.004*					-0.014	-0.003
					(0.009)						(0.011)	
Aberdeen			0.114	0.032	0.097	0.027			0.072	0.020	0.091	0.025
			(0.157)		(0.168)				(0.185)		(0.196)	
Barts			-0.027	-0.007	-0.068	-0.017			-0.293**	-0.069**	-0.345**	-0.079**
			(0.115)		(0.122)				(0.147)		(0.156)	
Brighton and Sussex			-0.064	-0.017	-0.080	-0.020			-0.294	-0.069	-0.270	-0.064
			(0.157)		(0.165)				(0.194)		(0.206)	
Bristol			0.112	0.031	0.077	0.021			0.094	0.026	0.067	0.019
			(0.133)		(0.148)				(0.154)		(0.173)	
Cambridge			0.011	0.003	0.072	0.020			-0.226	-0.055	-0.182	-0.045
			(0.154)		(0.169)				(0.192)		(0.210)	
Cardiff			0.087	0.024	-0.127	-0.032			-0.016	-0.004	-0.244	-0.059
			(0.121)		(0.141)				(0.149)		(0.175)	
Dundee			0.174	0.049	0.166	0.047			-0.122	-0.031	-0.087	-0.022
			(0.171)		(0.180)				(0.223)		(0.231)	
Edinburgh			0.177	0.050	0.181	0.052			0.139	0.039	0.116	0.033
			(0.147)		(0.156)				(0.178)		(0.188)	
Glasgow			0.149	0.042	0.147	0.041			0.049	0.013	0.074	0.021
			(0.147)		(0.158)				(0.187)		(0.199)	

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Table 3.8 – continued from previous page

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Hull York			-0.336**	-0.077**	-0.298*	-0.069*			-0.517**	-0.109**	-0.453**	-0.098**
			(0.154)		(0.160)				(0.203)		(0.210)	
Imperial			0.243**	0.071**	0.263**	0.077**			0.018	0.005	0.019	0.005
			(0.122)		(0.132)				(0.153)		(0.165)	
Keele			0.191	0.055	0.166	0.047			0.080	0.022	0.079	0.022
			(0.137)		(0.144)				(0.166)		(0.175)	
King's			0.105	0.029	0.078	0.021			-0.146	-0.037	-0.159	-0.040
			(0.120)		(0.131)				(0.150)		(0.163)	
Lancaster			-0.140	-0.035	-0.205	-0.050			-0.293	-0.069	-0.484	-0.104
			(0.229)		(0.256)				(0.270)		(0.318)	
Leeds			-0.009	-0.002	0.004	0.001			-0.062	-0.016	-0.095	-0.024
			(0.145)		(0.157)				(0.181)		(0.199)	
Leicester			-0.045	-0.012	-0.078	-0.020			-0.177	-0.044	-0.250	-0.060
			(0.124)		(0.132)				(0.159)		(0.171)	
Liverpool			-0.078	-0.020	-0.017	-0.004			-0.178	-0.044	-0.125	-0.032
			(0.130)		(0.139)				(0.163)		(0.174)	
Manchester			0.138	0.039	0.140	0.039			0.110	0.031	0.136	0.038
			(0.118)		(0.125)				(0.143)		(0.153)	
Newcastle			-0.019	-0.005	-0.033	-0.009			-0.137	-0.035	-0.125	-0.032
			(0.137)		(0.146)				(0.168)		(0.180)	
Norwich			0.033	0.009	0.005	0.001			-0.252	-0.061	-0.261	-0.062
			(0.135)		(0.142)				(0.177)		(0.186)	
Nottingham			0.179	0.051	0.218*	0.063*			0.020	0.006	0.029	0.008
			(0.114)		(0.125)				(0.138)		(0.149)	
Oxford			-0.169	-0.042	-0.117	-0.029			-0.324	-0.075	-0.265	-0.063
			(0.159)		(0.168)				(0.207)		(0.219)	
Peninsula			0.003	0.001	0.026	0.007			-0.191	-0.047	-0.145	-0.036
			(0.138)		(0.148)				(0.165)		(0.176)	
Queen's			-0.066	-0.017	-0.058	-0.015			-0.190	-0.047	-0.128	-0.032
			(0.197)		(0.221)				(0.257)		(0.287)	
Sheffield			-0.157	-0.039	-0.178	-0.044			-0.394**	-0.088**	-0.419*	-0.092*
			(0.151)		(0.165)				(0.193)		(0.214)	
Southampton			0.171	0.048	0.184	0.052			-0.060	-0.016	-0.082	-0.021
			(0.123)		(0.132)				(0.156)		(0.169)	
St George's			-0.081	-0.021	-0.052	-0.014			-0.185	-0.046	-0.168	-0.042
			(0.122)		(0.138)				(0.148)		(0.168)	
UCL			0.056	0.015	0.099	0.027			-0.143	-0.036	-0.095	-0.024
			(0.129)		(0.139)				(0.158)		(0.170)	
Warwick			-0.182	-0.045	-0.138	-0.034			-0.455**	-0.099**	-0.530**	-0.111**
			(0.137)		(0.156)				(0.179)		(0.206)	
Constant	-0.014		-0.320		0.217		-0.060		-0.408		0.238	
	(0.227)		(0.255)		(0.377)		(0.287)		(0.329)		(0.472)	
N	7,553		7,553		6,441		5,335		5,335		4,576	
Foundation School	NO		YES		YES		NO		YES		YES	
R^2	0.027		0.038		0.040		0.023		0.040		0.044	
Log-likelihood	-3709.750		-3667.713		-3110.213		-2381.299		-2340.442		-1986.752	
$Pr(y=1)$	0.203		0.203		0.202		0.173		0.172		0.171	

[a] Base outcomes: Gender: Man, Ethnicity:White, School: State, POLAR3:Other neighbourhood, Year Medical School: 2007, Year Process: 2015, Medical School: Birmingham, Foundation School: Birmingham

[b] SE: Standard Errors; AME: Average Marginal Effect

[c] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.9: Probit estimation results variable $PrimaryC$

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Woman	0.468***	0.179***	0.473***	0.178***	0.471***	0.176***	0.494***	0.187***	0.503***	0.186***	0.511***	0.188***
	(0.030)		(0.030)		(0.033)		(0.036)		(0.037)		(0.040)	
Age Process	0.028***	0.011***	0.028***	0.011***	0.029***	0.011***	0.031***	0.012***	0.030***	0.011***	0.034***	0.013***
	(0.006)		(0.006)		(0.007)		(0.007)		(0.007)		(0.009)	
Time Elapsed	0.071	0.027	0.024	0.009	0.068	0.025	0.102	0.039	0.030	0.011	0.069	0.025
	(0.054)		(0.056)		(0.064)		(0.063)		(0.066)		(0.076)	
BME	0.167***	0.064***	0.145***	0.055***	0.143***	0.054***	0.127***	0.048***	0.109**	0.041**	0.109**	0.040**
	(0.033)		(0.036)		(0.039)		(0.040)		(0.043)		(0.047)	
Parent Doctor	-0.140***	-0.053***	-0.138***	-0.052***	-0.123**	-0.046**	-0.129**	-0.049**	-0.126**	-0.047**	-0.114*	-0.042*
	(0.048)		(0.048)		(0.051)		(0.056)		(0.057)		(0.060)	
POLAR3: Low participation	-0.093	-0.035	-0.094	-0.035	-0.085	-0.032	-0.046	-0.017	-0.050	-0.019	-0.040	-0.015
	(0.074)		(0.075)		(0.083)		(0.087)		(0.090)		(0.098)	
POLAR3: Non-UK	-0.308***	-0.118***	-0.300***	-0.113***	-0.288***	-0.108***	-0.460***	-0.167***	-0.461***	-0.165***	-0.429***	-0.153***
	(0.070)		(0.071)		(0.082)		(0.093)		(0.095)		(0.109)	
School: Independent	-0.066*	-0.025*	-0.030	-0.011	-0.034	-0.013	-0.090**	-0.034**	-0.060	-0.022	-0.063	-0.023
	(0.038)		(0.038)		(0.041)		(0.044)		(0.046)		(0.048)	
School:Unknown	-0.019	-0.007	-0.001	-0.000	0.006	0.002	-0.052	-0.020	-0.040	-0.015	-0.030	-0.011
	(0.059)		(0.059)		(0.070)		(0.073)		(0.074)		(0.087)	
Graduate	-0.090*	-0.034*	-0.039	-0.015	-0.088	-0.033	-0.102*	-0.038*	-0.031	-0.012	-0.106	-0.039
	(0.050)		(0.054)		(0.063)		(0.061)		(0.066)		(0.077)	
Year Process: 2012	0.046	0.018	-0.061	-0.023	-1.139*	-0.360*	-0.266	-0.096	-0.435	-0.152	-0.991	-0.297
	(0.191)		(0.193)		(0.666)		(0.282)		(0.281)		(0.747)	
Year Process: 2013	0.324***	0.123***	0.249***	0.093***	0.272**	0.101**	0.340***	0.129***	0.249***	0.093***	0.226*	0.084*
	(0.072)		(0.077)		(0.108)		(0.086)		(0.093)		(0.126)	
Year Process: 2014	0.182***	0.070***	0.125***	0.047***	0.175***	0.066***	0.191***	0.072***	0.119**	0.044**	0.161***	0.060***
	(0.037)		(0.039)		(0.044)		(0.044)		(0.047)		(0.052)	
Year Medical School: 2008	0.127***	0.049***	0.066*	0.025*	0.119***	0.045***	0.097**	0.037**	0.028	0.010	0.071	0.026
	(0.036)		(0.039)		(0.044)		(0.043)		(0.047)		(0.052)	
Top5 Uni	-0.179***	-0.068***					-0.157***	-0.060***				
	(0.045)						(0.055)					
UKCAT Score					-0.041***	-0.015***					-0.042***	-0.016***
					(0.008)						(0.010)	
Aberdeen			0.166	0.063	-0.020	-0.007			0.198	0.074	0.015	0.005
			(0.136)		(0.145)				(0.158)		(0.169)	
Barts			0.245**	0.093**	0.252**	0.094**			0.345***	0.129***	0.367***	0.136***
			(0.102)		(0.109)				(0.124)		(0.133)	
Brighton and Sussex			0.114	0.043	0.095	0.036			0.062	0.023	0.017	0.006
			(0.132)		(0.139)				(0.156)		(0.165)	
Bristol			0.113	0.043	0.120	0.045			0.158	0.059	0.152	0.056
			(0.118)		(0.132)				(0.139)		(0.155)	
Cambridge			-0.292**	-0.109**	-0.228	-0.085			-0.192	-0.069	-0.084	-0.031
			(0.141)		(0.158)				(0.173)		(0.192)	
Cardiff			0.159	0.060	0.174	0.065			0.221*	0.082*	0.231	0.086
			(0.107)		(0.126)				(0.129)		(0.152)	
Dundee			0.098	0.037	-0.026	-0.010			0.145	0.054	-0.035	-0.013
			(0.148)		(0.156)				(0.180)		(0.188)	
Edinburgh			-0.178	-0.067	-0.196	-0.073			-0.127	-0.046	-0.169	-0.061
			(0.133)		(0.142)				(0.160)		(0.171)	
Glasgow			-0.012	-0.005	-0.080	-0.030			-0.051	-0.019	-0.144	-0.052
			(0.131)		(0.142)				(0.159)		(0.172)	

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Table 3.9 – continued from previous page

	Sample 1: All Doctors						Sample 2: Single Application Only					
	(1)		(2)		(3)		(1)		(2)		(3)	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Hull York			0.375***	0.140***	0.361***	0.134***			0.348**	0.130**	0.326*	0.121*
			(0.131)		(0.139)				(0.161)		(0.171)	
Imperial			-0.025	-0.009	0.014	0.005			-0.130	-0.047	-0.063	-0.023
			(0.113)		(0.123)				(0.142)		(0.153)	
Keele			0.009	0.003	-0.028	-0.010			0.090	0.033	0.035	0.013
			(0.122)		(0.128)				(0.147)		(0.154)	
King's			0.004	0.001	0.031	0.012			0.012	0.004	0.049	0.018
			(0.108)		(0.118)				(0.131)		(0.142)	
Lancaster			0.081	0.031	0.010	0.004			0.077	0.028	-0.033	-0.012
			(0.189)		(0.210)				(0.216)		(0.243)	
Leeds			0.117	0.045	0.117	0.044			0.172	0.064	0.198	0.073
			(0.127)		(0.137)				(0.153)		(0.166)	
Leicester			0.285***	0.107***	0.238**	0.089**			0.276**	0.103**	0.231*	0.085*
			(0.108)		(0.115)				(0.131)		(0.139)	
Liverpool			0.216*	0.082*	0.130	0.049			0.199	0.074	0.132	0.049
			(0.111)		(0.121)				(0.135)		(0.146)	
Manchester			0.183*	0.069*	0.196*	0.074*			0.234*	0.087*	0.224*	0.083*
			(0.105)		(0.113)				(0.126)		(0.136)	
Newcastle			0.272**	0.103**	0.330***	0.122***			0.257*	0.096*	0.303**	0.113**
			(0.116)		(0.124)				(0.141)		(0.150)	
Norwich			0.038	0.015	0.021	0.008			0.119	0.044	0.109	0.040
			(0.118)		(0.125)				(0.144)		(0.153)	
Nottingham			0.106	0.040	0.105	0.039			0.214*	0.080*	0.208	0.077
			(0.102)		(0.113)				(0.119)		(0.130)	
Oxford			-0.093	-0.035	0.079	0.030			-0.333*	-0.116*	-0.156	-0.056
			(0.141)		(0.150)				(0.187)		(0.198)	
Peninsula			0.264**	0.100**	0.281**	0.105**			0.390***	0.146***	0.406***	0.150***
			(0.121)		(0.133)				(0.143)		(0.156)	
Queen's			0.034	0.013	-0.098	-0.037			0.091	0.034	-0.004	-0.001
			(0.165)		(0.180)				(0.205)		(0.222)	
Sheffield			0.378***	0.141***	0.351**	0.130**			0.362**	0.135**	0.385**	0.143**
			(0.134)		(0.144)				(0.157)		(0.169)	
Southampton			0.122	0.046	0.054	0.020			0.122	0.045	0.050	0.018
			(0.110)		(0.119)				(0.131)		(0.142)	
St George's			0.127	0.048	0.022	0.008			0.185	0.069	0.086	0.032
			(0.105)		(0.120)				(0.125)		(0.143)	
UCL			-0.148	-0.056	-0.074	-0.028			-0.124	-0.045	-0.060	-0.022
			(0.118)		(0.130)				(0.143)		(0.157)	
Warwick			0.086	0.033	0.057	0.022			0.097	0.036	0.065	0.024
			(0.118)		(0.136)				(0.143)		(0.164)	
Constant	-1.206***		-1.016***		-0.177		-1.503***		-1.329***		-0.524	
	(0.197)		(0.222)		(0.333)		(0.235)		(0.265)		(0.399)	
N	7,553		7,553		6,441		5,335		5,335		4,576	
R^2	0.038		0.050		0.055		0.043		0.061		0.066	
Log-likelihood	-5025.496		-4960.539		-4208.379		-3520.399		-3454.999		-2950.198	
$Pr(y=1)$	0.529		0.529		0.528		0.458		0.457		0.459	

[a] Base outcomes: Gender: Man, Ethnicity:White, School: State, POLAR3:Other neighbourhood, Year Medical School: 2007, Year Process: 2015, Medical School: Birmingham, Foundation School: Birmingham

[b] SE: Standard Errors; AME: Average Marginal Effect

[c] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.10: Probit Estimation results variable $Applimore$

	Sample 1: All Doctors											
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Woman	0.029	0.010	-0.090***	-0.028***	-0.010	-0.003	-0.089***	-0.028***	0.057*	0.019*	-0.027	-0.009
	(0.032)		(0.033)		(0.032)		(0.033)		(0.032)		(0.032)	
BME	0.175***	0.059***	0.114***	0.036***	0.202***	0.066***	0.147***	0.047***	0.149***	0.049***	0.193***	0.063***
	(0.037)		(0.038)		(0.037)		(0.037)		(0.037)		(0.037)	
Age Process	0.017***	0.006***	0.011*	0.003*	0.018***	0.006***	0.011*	0.004*	0.019***	0.006***	0.016***	0.005***
	(0.006)		(0.006)		(0.006)		(0.006)		(0.006)		(0.006)	
Time Elapsed	-0.115*	-0.039*	-0.110*	-0.034*	-0.142**	-0.046**	-0.128**	-0.041**	-0.094	-0.031	-0.138**	-0.045**
	(0.060)		(0.063)		(0.061)		(0.062)		(0.060)		(0.060)	
Parent Doctor	-0.080	-0.027	-0.056	-0.017	-0.070	-0.023	-0.048	-0.015	-0.094*	-0.031*	-0.066	-0.021
	(0.052)		(0.053)		(0.053)		(0.053)		(0.052)		(0.052)	
POLAR3: Low participation	0.010	0.003	0.031	0.010	0.019	0.006	0.037	0.012	0.004	0.001	0.019	0.006
	(0.079)		(0.082)		(0.080)		(0.081)		(0.079)		(0.080)	
POLAR3: Non-UK	0.337***	0.120***	0.409***	0.136***	0.338***	0.117***	0.430***	0.148***	0.309***	0.109***	0.359***	0.126***
	(0.072)		(0.073)		(0.073)		(0.073)		(0.072)		(0.073)	
School: Private	-0.029	-0.010	-0.032	-0.010	-0.034	-0.011	-0.028	-0.009	-0.031	-0.010	-0.023	-0.008
	(0.041)		(0.042)		(0.042)		(0.042)		(0.041)		(0.041)	
School:Unknown	0.063	0.021	0.072	0.023	0.046	0.015	0.064	0.021	0.056	0.019	0.074	0.025
	(0.061)		(0.063)		(0.062)		(0.062)		(0.062)		(0.062)	
Graduate	0.040	0.014	0.035	0.011	0.035	0.011	0.050	0.016	0.032	0.010	0.054	0.018
	(0.054)		(0.057)		(0.055)		(0.056)		(0.055)		(0.055)	
Year Process: 2012	-0.096	-0.031	-0.066	-0.020	-0.103	-0.032	-0.101	-0.032	-0.101	-0.032	-0.104	-0.033
	(0.189)		(0.189)		(0.188)		(0.186)		(0.191)		(0.194)	
Year Process: 2013	-0.084	-0.028	-0.140*	-0.042*	-0.092	-0.029	-0.151*	-0.047*	-0.083	-0.027	-0.091	-0.029
	(0.078)		(0.080)		(0.079)		(0.080)		(0.078)		(0.079)	
Year Process: 2014	0.009	0.003	-0.008	-0.002	0.019	0.006	-0.021	-0.007	0.019	0.006	0.005	0.002
	(0.041)		(0.043)		(0.041)		(0.042)		(0.041)		(0.041)	
Year Medical School: 2008	0.010	0.003	0.015	0.005	0.010	0.003	-0.007	-0.002	0.021	0.007	0.000	0.000
	(0.040)		(0.041)		(0.040)		(0.041)		(0.040)		(0.040)	
$Runtho$			0.829***	0.258***								
			(0.035)									
$BottomInc$					0.677***	0.219***						
					(0.043)							
$PrimaryC$							0.653***	0.208***				
							(0.033)					
$Surgical$									0.384***	0.127***		
									(0.038)			
$TopInc$											-0.695***	-0.228***
											(0.059)	
Constant	-0.881***		-1.167***		-0.987***		-1.004***		-1.021***		-0.719***	
	(0.221)		(0.229)		(0.224)		(0.226)		(0.222)		(0.223)	
N	7,553		7,553		7,553		7,553		7,553		7,553	
R^2	0.028		0.094		0.056		0.072		0.040		0.045	
Log-Likelihood	-4442.520		-4144.842		-4317.081		-4244.562		-4391.636		-4367.910	
$Pr(y=1)$	0.294		0.294		0.294		0.294		0.294		0.294	

[a] Base outcomes: Gender: Man, Ethnicity:White, School: State, POLAR3:Other neighbourhood, Year Medical School: 2007, Year Process: 2015, Medical School: Birmingham, Foundation School: Birmingham
[b] SE: Standard Errors; AME: Average Marginal Effect
[c] P-values: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table 3.11: Original and transformed interview scores by specialty

	Original Interview Score (IS)						**Transformation 1 (IS^{T1})**				**Transformation 2 (IS^{T2})**				
	Mean	Std. Dev.	Min	Min*	Max	Obs	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Obs (1) &(2)
ACCM - Emergency Medicine	156.69	60.74	0	106	235	430	0.549	0.189	0	1	0.284	0.446	-1.225	1.289	381
Broad Based Training	135.88	46.46	0	39	186.6	105	0.722	0.202	0	1	0.197	0.638	-2.021	1.091	98
Cardio-thoracic surgery	267.97	114.4	0	238	471.4	10	0.256	0.295	0	1	0.368	0.376	-0.09	1.17	9
Clinical radiology	92.95	33.19	0	47	147	262	0.549	0.171	0	1	0.243	0.524	-1.363	1.628	239
Community Sexual and Reproductive Health	76.33	6.03	70	70	82	3	0.528	0.502	0	1	0.291	0.58	-0.177	0.94	3
Core Anaesthetics Training	134.31	22.14	79	79	207	341	0.432	0.173	0	1	0.077	0.86	-2.246	3.838	341
Core Medical Training	47.37	9.51	0	26	83.9	910	0.377	0.143	0	1	0.052	0.82	-2.246	3.838	901
Core Psychiatry Training	48.98	13.47	0	32	67	175	0.561	0.209	0	1	0.186	0.533	-1.26	1.337	166
Core Surgical Training	145.12	39.01	0	75	211	1025	0.568	0.166	0	1	0.175	0.576	-1.798	1.903	977
General practice	50.37	39.74	0	1	69	393	0.639	0.37	0	1	0.262	0.809	-1.651	1.701	321
Histopathology	386.59	169.8	0	231	546	56	0.698	0.202	0	1	0.363	0.404	-1.581	0.903	48
Neurosurgery	135.27	29.7	0	0	172.3	37	0.785	0.172	0	1	0.263	0.505	-1.184	1.2467	37
Obstetrics and gynaecology	84.48	18.74	0	59	110	162	0.552	0.22	0	1	0.159	0.575	-1.359	1.362	157
Ophthalmology	106.91	20.79	0	47.3	159	146	0.54	0.169	0	1	0.039	0.828	-2.641	1.736	145
Paediatrics	119.48	30.87	0	84	152	275	0.616	0.205	0	1	0.213	0.449	-1.132	1.3	261
Public health medicine	50.22	16.14	0	40.2	64	36	0.613	0.218	0	1	0.306	0.296	-0.371	0.853	33

* Real minimum interview scores observed in the process. Some specializations report no-shows with a zero.

Table 3.12: Variables included in each Specification of the selection stage analysis

Specification (1)	*Woman*, *BME*, *Age Process*, *Time Elapsed*, *AppliMore*, *Parent Doctor*, *POLAR3*, *School*, *Graduate*, *Top 5 Uni*, *Year Start* and *Year Process*
Specification (2)	(1) + *Medical School*, *Foundation School* and *Specialty* fixed effects
Specification (3)	(2) + *Shortlisting Score*
Specification (4)	(3) + *UKCAT Score*

Table 3.13: Descriptive statistics: selection stage

	Doctors who did a single interview					All doctors		
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.
Gender: Man	3,053	0.463	0.499	0	1	3,552	0.470	0.499
Gender: Woman	3,053	0.537	0.499	0	1	3,552	0.530	0.499
Ethnicity: White	3,053	0.677	0.468	0	1	3,552	0.667	0.471
Ethnicity: BME	3,053	0.323	0.468	0	1	3,552	0.333	0.471
Age Process	3,053	27.952	3.470	24	54	3,552	28.043	3.543
Time Elapsed	3,053	2.064	0.249	2	4	3,552	2.062	0.246
Parent doctor	3,053	0.105	0.307	0	1	3,552	0.101	0.301
School: School	3,053	0.629	0.483	0	1	3,552	0.622	0.485
School: Independent	3,053	0.193	0.395	0	1	3,552	0.186	0.389
School: Unknown	3,053	0.178	0.382	0	1	3,552	0.192	0.394
POLAR3: Low participation Neighbourhood	3,035	0.043	0.204	0	1	3,531	0.043	0.204
POLAR3: Non-UK Neighbourhood	3,035	0.121	0.326	0	1	3,531	0.132	0.339
POLAR3: Other Neighbourhood	3,035	0.836	0.371	0	1	3,531	0.825	0.380
Graduated on entry	3,053	0.343	0.475	0	1	3,552	0.353	0.478
Top 5 University	3,053	0.123	0.329	1	2	3,553	0.127	0.333
UKCAT Score	2,446	25.140	2.253	16.3	32.5	2,818	25.147	2.266
Year Medical School: 2007	3,053	0.730	0.444	0	1	3,552	0.737	0.440
Year Medical School: 2008	3,053	0.270	0.444	0	1	3,552	0.263	0.440
Interview Score transformed (1)	3,053	0.538	0.217	0	1	3,552	0.532	0.211
Interview Score transformed (2)	3,053	0.198	0.707	-2.6	3.8	3,552	0.180	0.689
Shortlisting Score transformed (1)	1,483	0.463	0.216	0.0	1	1,850	0.461	0.213
Shortlisting Score transformed (2)	1,483	-0.018	0.954	-3.0	4.1	1,850	-0.013	0.948
Nr Applications	3,053	1.379	0.622	1	5	3,552	1.531	0.757
AppliMore	3,053	0.314	0.464	0	1	3,553	0.410	0.757
Year Process: 2012	3,053	0.013	0.115	0	1	3,552	0.015	0.123
Year Process: 2013	3,053	0.140	0.347	0	1	3,552	0.148	0.355
Year Process: 2014	3,053	0.487	0.500	0	1	3,552	0.493	0.500
Year Process: 2015	3,053	0.360	0.480	0	1	3,552	0.344	0.475

Table 3.14: Descriptive statistics by ethnicity and gender: selection stage

	White			BME			Men			Women		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Gender: Man	2,066	0.443	0.497	987	0.506	0.500	-	-	-	-	-	-
Gender: Woman	2,066	0.557	0.497	987	0.494	0.500	-	-	-	-	-	-
Ethnicity: White	-	-	-	-	-	-	1,415	0.647	0.478	1,638	0.702	0.457
Ethnicity: BME	-	-	-	-	-	-	1,415	0.353	0.478	1,638	0.298	0.457
Age Process	2,066	28.166	3.651	987	27.505	3.010	1,415	28.124	3.719	1,638	27.803	3.234
Time Elapsed	2,066	2.069	0.259	987	2.055	0.228	1,415	2.059	0.242	1,638	2.068	0.255
Parent doctor	2,066	0.083	0.276	987	0.153	0.360	1,415	0.120	0.325	1,638	0.093	0.290
School: State	2,066	0.684	0.465	987	0.515	0.500	1,415	0.615	0.487	1,638	0.642	0.480
School: Independent	2,066	0.187	0.390	987	0.205	0.404	1,415	0.213	0.409	1,638	0.176	0.381
School:Unknown	2,066	0.129	0.335	987	0.281	0.450	1,415	0.172	0.378	1,638	0.183	0.386
POLAR3: Low participation Neighbourhood	2,051	0.048	0.214	984	0.034	0.180	1,405	0.047	0.212	1,630	0.040	0.197
POLAR3: Non-UK Neighbourhood	2,051	0.051	0.220	984	0.266	0.442	1,405	0.112	0.315	1,630	0.129	0.335
POLAR3: Other Neighbourhood	2,051	0.901	0.299	984	0.700	0.458	1,405	0.841	0.366	1,630	0.831	0.375
Graduated on entry	2,066	0.389	0.488	987	0.247	0.432	1,415	0.329	0.470	1,638	0.355	0.479
UKCAT Score	1,647	25.347	2.189	799	24.713	2.325	1,130	25.343	2.231	1,316	24.965	2.259
Top 5 University	2,066	0.129	0.336	987	0.111	0.315	1,415	0.131	0.337	1,638	0.117	0.322
Year Medical School: 2007	2,066	0.733	0.443	987	0.724	0.447	1,415	0.726	0.446	1,638	0.734	0.442
Year Medical School: 2008	2,066	0.267	0.443	987	0.276	0.447	1,415	0.274	0.446	1,638	0.266	0.442
Interview Score transformed (1)	2,066	0.561	0.216	987	0.488	0.212	1,415	0.523	0.214	1,638	0.550	0.219
Interview Score transformed (2)	2,066	0.277	0.672	987	0.032	0.749	1,415	0.149	0.727	1,638	0.241	0.686
Shortlisting Score transformed (1)	969	0.478	0.227	514	0.435	0.191	630	0.463	0.209	853	0.463	0.221
Shortlisting Score transformed (2)	969	0.053	0.969	514	-0.153	0.909	630	-0.038	0.957	853	-0.004	0.952
Nr Applications	2,066	1.336	0.581	987	1.467	0.693	1,415	1.341	0.596	1,638	1.411	0.643
AppliMore	2,066	0.286	0.452	987	0.373	0.484	1,416	0.283	0.451	1,638	0.341	0.474
Year Process: 2012	2,066	0.007	0.085	987	0.026	0.160	1,415	0.013	0.112	1,638	0.014	0.118
Year Process: 2013	2,066	0.152	0.359	987	0.114	0.319	1,415	0.140	0.347	1,638	0.139	0.346
Year Process: 2014	2,066	0.515	0.500	987	0.430	0.495	1,415	0.428	0.495	1,638	0.538	0.499
Year Process: 2015	2,066	0.327	0.469	987	0.430	0.495	1,415	0.419	0.494	1,638	0.309	0.462

Table 3.15: OLS estimation results

	IS^{T1}				IS^{T2}			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Woman	0.0393***	0.0338***	0.0320**	0.0338**	0.1171***	0.1142***	0.1172**	0.1247**
	(0.0075)	(0.0070)	(0.0105)	(0.0118)	(0.0255)	(0.0263)	(0.0424)	(0.0480)
Age Process	0.0001	-0.0019	-0.0022	-0.0020	-0.0082	-0.0095*	-0.0151	-0.0192
	(0.0015)	(0.0014)	(0.0020)	(0.0029)	(0.0047)	(0.0048)	(0.0078)	(0.0119)
Time Elapsed	-0.0275	-0.0206	-0.0312	0.0130	-0.0639	-0.0585	-0.0507	0.1182
	(0.0167)	(0.0175)	(0.0332)	(0.0359)	(0.0575)	(0.0592)	(0.1223)	(0.1367)
BME	-0.0595***	-0.0556***	-0.0457***	-0.0385**	-0.1971***	-0.2114***	-0.2019***	-0.1750**
	(0.0084)	(0.0083)	(0.0128)	(0.0141)	(0.0290)	(0.0311)	(0.0527)	(0.0589)
Parent Doctor	0	0.0012	-0.0095	-0.006	0.0065	0.007	-0.0482	-0.0442
	(0.0120)	(0.0112)	(0.0172)	(0.0172)	(0.0425)	(0.0423)	(0.0694)	(0.0708)
AppliMore	-0.0198*	-0.0299***	-0.0151	-0.0153	-0.0841**	-0.0873**	-0.0456	-0.0429
	(0.0080)	(0.0077)	(0.0137)	(0.0149)	(0.0273)	(0.0284)	(0.0585)	(0.0662)
POLAR3:Low participation	-0.0081	-0.0078	0.0073	0.0145	0.0044	0.0065	0.0460	0.0658
	(0.0200)	(0.0191)	(0.0277)	(0.0306)	(0.0647)	(0.0661)	(0.1043)	(0.1248)
POLAR3:Non-UK	-0.0502**	-0.0365*	-0.0153	-0.0149	-0.1792**	-0.1762**	-0.1336	-0.1241
	(0.0175)	(0.0161)	(0.0235)	(0.0267)	(0.0607)	(0.0622)	(0.0972)	(0.1118)
School: Independent	0.0178	0.0017	0.0136	0.0148	0.0452	0.0100	0.0718	0.0774
	(0.0097)	(0.0092)	(0.0148)	(0.0155)	(0.0346)	(0.0351)	(0.0617)	(0.0653)
School:Unknown	-0.0086	-0.0161	-0.0263	0.0156	-0.0156	-0.0272	-0.0242	0.0860
	(0.0147)	(0.0132)	(0.0188)	(0.0236)	(0.0475)	(0.0484)	(0.0754)	(0.0976)
Graduate	0.0485***	0.0312*	-0.0086	-0.0384	0.1495***	0.1084*	-0.0236	-0.0811
	(0.0125)	(0.0124)	(0.0175)	(0.0212)	(0.0400)	(0.0441)	(0.0702)	(0.0878)
Year Process: 2012	-0.0914**	0.0160	0.1239**	0.3029*	-0.2144	-0.1022	-0.1286	0.4547
	(0.0342)	(0.0309)	(0.0474)	(0.1497)	(0.1180)	(0.1216)	(0.1999)	(0.3856)
Year Process: 2013	-0.0024	0.0809***	0.2232***	0.3330***	-0.0501	0.0610	0.2016	0.5555***
	(0.0165)	(0.0215)	(0.0344)	(0.0432)	(0.0504)	(0.0720)	(0.1309)	(0.1640)
Year Process: 2014	-0.1308***	-0.0229	0.0661*	0.0541	-0.2873***	-0.2106***	-0.2872*	-0.3619*
	(0.0091)	(0.0127)	(0.0294)	(0.0327)	(0.0318)	(0.0511)	(0.1257)	(0.1436)
Year Medical School: 2008	-0.0549***	-0.0480***	-0.0381*	-0.0168	-0.1463***	-0.1315***	-0.1020	-0.0253
	(0.0099)	(0.0098)	(0.0148)	(0.0174)	(0.0341)	(0.0355)	(0.0577)	(0.0686)
Top 5 University	0.0158				0.0528			
	(0.0116)				(0.0398)			
Shortlisting (SC^{T1}/SC^{T2})			0.2374***	0.2384***			0.1891***	0.1912***
			(0.0328)	(0.0369)			(0.0241)	(0.0289)
UKCAT Score				0.0067**				0.0263*
				(0.0026)				(0.0107)
Constant	0.6628***	0.5489***	0.3894***	0.0987	0.7331***	0.8505***	1.0310**	0.0768
	(0.0533)	(0.0565)	(0.0968)	(0.1315)	(0.1728)	(0.1939)	(0.3639)	(0.5299)
N	3,035	3,035	1,479	1,152	3,035	3,035	1,479	1,152
R^2	0.132	0.31	0.427	0.426	0.079	0.111	0.16	0.178
Medical /Foundation School	NO	YES	YES	YES	NO	YES	YES	YES
Specialty Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Shorlisting Score	NO	NO	YES	YES	NO	NO	YES	YES
UKCAT score	NO	NO	NO	YES	NO	NO	NO	YES

[a] Base outcomes: Gender: Man, Ethnicity:White, School: State, POLAR3:Other neighbourhood,Year Medical School:2007, Year Process:2015
[b] IS^{T1}, IS^{T2}: Interview score transformation 1 and 2
[c] Robust standard errors in parenthesis
[d] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.16: Results of the aggregate Oaxaca-Blinder decomposition: ethnicity

	OB decomposition IS^{T1}				OB decomposition IS^{T2}			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Estimated Mean White doctors	0.5612***	0.5612***	0.5287***	0.5118***	0.2777***	0.2777***	0.2364***	0.2109***
	(0.0048)	(0.0048)	(0.0079)	(0.0088)	(0.0149)	(0.0149)	(0.0248)	(0.0286)
Estimated Mean BME doctors	0.4881***	0.4881***	0.4465***	0.4533***	0.0323	0.0323	-0.0299	-0.0075
	(0.0067)	(0.0068)	(0.0099)	(0.0110)	(0.0239)	(0.0239)	(0.0373)	(0.0422)
Difference	0.0731***	0.0731***	0.0823***	0.0585***	0.2454***	0.2454***	0.2663***	0.2183***
	(0.0083)	(0.0083)	(0.0127)	(0.0141)	(0.0281)	(0.0281)	(0.0448)	(0.0509)
Explained	0.0139***	0.0180**	0.0360***	0.0205	0.0513***	0.0358**	0.0667	0.0436
	(0.0042)	(0.0061)	(0.0109)	(0.0120)	(0.0129)	(0.0182)	(0.0343)	(0.0386)
Unexplained	0.0592***	0.0551***	0.0463***	0.0379**	0.1941***	0.2096***	0.1996***	0.1747**
	(0.0084)	(0.0081)	(0.0122)	(0.0134)	(0.0288)	(0.0303)	(0.0499)	(0.0559)
N	3,035	3,035	1,479	1,152	3,035	3,035	1,479	1,152
Demographic covariates	YES	YES	YES	YES	YES	YES	YES	YES
Socio-economic covariates	YES	YES	YES	YES	YES	YES	YES	YES
Medical School Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Foundation School Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Speciality Interview Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Shortlisting Score	NO	NO	YES	YES	NO	NO	YES	YES
UKCAT score	NO	NO	NO	YES	NO	NO	NO	YES

Robust standard errors in parenthesis
P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.17: Results of the aggregate Oaxaca-Blinder decomposition: gender

	OB decomposition IS^{T1}				OB decomposition IS^{T2}			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Estimated mean men	0.5233***	0.5233***	0.4832***	0.4700***	0.1492***	0.1492***	0.0818*	0.0618
	(0.0057)	(0.0057)	(0.0096)	(0.0108)	(0.0194)	(0.0194)	(0.0334)	(0.0393)
Estimated mean women	0.5497***	0.5497***	0.5126***	0.5064***	0.2403***	0.2403***	0.1897***	0.1862***
	(0.0054)	(0.0054)	(0.0083)	(0.0090)	(0.0170)	(0.0170)	(0.0268)	(0.0297)
Difference	-0.0265***	-0.0265***	-0.0294*	-0.0364**	-0.0911***	-0.0911***	-0.1079*	-0.1244*
	(0.0079)	(0.0079)	(0.0127)	(0.0141)	(0.0258)	(0.0258)	(0.0428)	(0.0493)
Explained	0.0118***	0.0070	0.0020	-0.0028	0.0230**	0.0217	0.0068	-0.0007
	(0.0032)	(0.0051)	(0.0091)	(0.0103)	(0.0087)	(0.0122)	(0.0230)	(0.0283)
Unexplained	-0.0382***	-0.0334***	-0.0314**	-0.0337**	-0.1141***	-0.1128***	-0.1147**	-0.1236**
	(0.0075)	(0.0069)	(0.0101)	(0.0114)	(0.0254)	(0.0257)	(0.0408)	(0.0461)
N	3,035	3,035	1,479	1,152	3,035	3,035	1,479	1,152
Demographic covariates	YES	YES	YES	YES	YES	YES	YES	YES
Socio-economic covariates	YES	YES	YES	YES	YES	YES	YES	YES
Medical School Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Foundation School Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Speciality Interview Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Shortlisting Score	NO	NO	YES	YES	NO	NO	YES	YES
UKCAT score	NO	NO	NO	YES	NO	NO	NO	YES

Robust standard errors in parenthesis
P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.18: Robustness Check. Results of the aggregate Oaxaca-Blinder decomposition: gender

	CST[a]: OB decomposition IS^{T1}			CMT[b]: OB decomposition IS^{T1}			
	(1)	(2)	(3)	(1)	(2)	(3)	(4)
Estimated mean men	0.5659***	0.5659***	0.4897***	0.3751***	0.3751***	0.3751***	0.3849***
	(0.0078)	(0.0078)	(0.0186)	(0.0093)	(0.0093)	(0.0093)	(0.0110)
Estimated mean women	0.5762***	0.5762***	0.5531***	0.3808***	0.3808***	0.3813***	0.3840***
	(0.0091)	(0.0091)	(0.0213)	(0.0070)	(0.0070)	(0.0070)	(0.0076)
Difference	-0.0103	-0.0103	-0.0634*	-0.0057	-0.0057	-0.0061	0.0009
	(0.0119)	(0.0119)	(0.0282)	(0.0116)	(0.0116)	(0.0116)	(0.0134)
Explained	0.0103*	0.0074	-0.0079	0.0063	0.0052	0.0062	0.0163
	(0.0049)	(0.0073)	(0.0295)	(0.0083)	(0.0090)	(0.0092)	(0.0111)
Unexplained	-0.0206	-0.0177	-0.0555*	-0.0121	-0.0109	-0.0124	-0.0154
	(0.0117)	(0.0114)	(0.0245)	(0.0083)	(0.0083)	(0.0081)	(0.0092)
N	798	798	140	687	687	686	535
Demographic covariates	YES	YES	YES	YES	YES	YES	YES
Socio-economic covariates	YES	YES	YES	YES	YES	YES	YES
Medical School Dummies	NO	YES	YES	NO	YES	YES	YES
Foundation School Dummies	NO	YES	YES	NO	YES	YES	YES
Speciality Interview Dummies	NO	YES	YES	NO	YES	YES	YES
Shortlisting Score	NO	NO	YES	NO	NO	YES	YES
UKCAT score	NO	NO	NO	NO	NO	NO	YES

[a]CST: Core surgical training; [b]CMT: Core medical training.
Robust standard errors in parenthesis
P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.19: Robustness Check. Results of the aggregate Oaxaca-Blinder: ethnicity

	CST[a]: OB decomposition IS^{T1}			CMT[b]: OB decomposition IS^{T1}			
	(1)	(2)	(3)	(1)	(2)	(3)	(4)
Estimated Mean White doctors	0.5918***	0.5918***	0.5377***	0.3887***	0.3887***	0.3891***	0.3906***
	(0.0073)	(0.0073)	(0.0194)	(0.0064)	(0.0064)	(0.0064)	(0.0070)
Estimated Mean BME doctors	0.5377***	0.5377***	0.4976***	0.3579***	0.3579***	0.3579***	0.3699***
	(0.0096)	(0.0096)	(0.0189)	(0.0108)	(0.0108)	(0.0108)	(0.0131)
Difference	0.0541***	0.0541***	0.0401	0.0308*	0.0308*	0.0312*	0.0207
	(0.0121)	(0.0121)	(0.0271)	(0.0125)	(0.0125)	(0.0125)	(0.0148)
Explained	0.0066	0.0042	-0.0179	-0.0074	-0.0134	-0.0106	-0.0316*
	(0.0059)	(0.0084)	(0.0319)	(0.0104)	(0.0113)	(0.0114)	(0.0134)
Unexplained	0.0475***	0.0498***	0.0580*	0.0382***	0.0442***	0.0419***	0.0523***
	(0.0119)	(0.0122)	(0.0253)	(0.0097)	(0.0099)	(0.0096)	(0.0110)
N	798	798	140	687	687	686	535
Demographic covariates	YES	YES	YES	YES	YES	YES	YES
Socio-economic covariates	YES	YES	YES	YES	YES	YES	YES
Medical School Dummies	NO	YES	YES	NO	YES	YES	YES
Foundation School Dummies	NO	YES	YES	NO	YES	YES	YES
Speciality Interview Dummies	NO	YES	YES	NO	YES	YES	YES
Shortlisting Score	NO	NO	YES	NO	NO	YES	YES
UKCAT score	NO	NO	NO	NO	NO	NO	YES

[a]CST: Core surgical training; [b]CMT: Core medical training.
Robust standard errors in parenthesis
P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.20: Robustness Check. Results of the aggregate Oaxaca-Blinder: random group allocation

	OB decomposition IS^{T1}				OB decomposition IS^{T2}			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Estimated mean group 1	0.5339***	0.5339***	0.4955***	0.4870***	0.1836***	0.1836***	0.1278***	0.1166***
	(0.0056)	(0.0056)	(0.0089)	(0.0098)	(0.0183)	(0.0183)	(0.0300)	(0.0344)
Estimated mean group 2	0.5410***	0.5410***	0.5049***	0.4957***	0.2125***	0.2125***	0.1604***	0.1528***
	(0.0056)	(0.0056)	(0.0089)	(0.0098)	(0.0181)	(0.0181)	(0.0293)	(0.0332)
Difference	-0.0071	-0.0071	-0.0095	-0.0087	-0.0290	-0.0290	-0.0326	-0.0363
	(0.0079)	(0.0079)	(0.0126)	(0.0139)	(0.0257)	(0.0257)	(0.0419)	(0.0478)
Explained	0.0016	0.0016	-0.0044	-0.0074	0.0066	-0.0004	-0.0288	-0.0478
	(0.0029)	(0.0047)	(0.0089)	(0.0100)	(0.0076)	(0.0106)	(0.0214)	(0.0262)
Unexplained	-0.0088	-0.0088	-0.0050	-0.0013	-0.0356	-0.0285	-0.0038	0.0115
	(0.0074)	(0.0066)	(0.0096)	(0.0106)	(0.0247)	(0.0246)	(0.0390)	(0.0439)
N	3,035	3,035	1,479	1,152	3,035	3,035	1,479	1,152
Demographic covariates	YES	YES	YES	YES	YES	YES	YES	YES
Socio-economic covariates	YES	YES	YES	YES	YES	YES	YES	YES
Medical School Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Foundation School Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Speciality Interview Dummies	NO	YES	YES	YES	NO	YES	YES	YES
Shortlisting Score	NO	NO	YES	YES	NO	NO	YES	YES
UKCAT score	NO	NO	NO	YES	NO	NO	NO	YES

Robust standard errors in parenthesis
P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Chapter 4

Why are there so few female surgeons? An empirical analysis for the Spanish resident market

4.1 Introduction

Over the past several decades the medical profession in most developed countries has experienced a steady increase in the number of female physicians. The mean share of female doctors in the OECD countries incrementally increased from 37.9% in year 2000 to 44.5% in 2013 (OECD Indicators 2015). Spain, in particular, has experienced this phenomenon in more of an extreme, as the share of female doctors has risen from 36.8% in 2000 to 50.2% in 2013. With regard to junior doctors, already in 1991, the percentage of males and females allocated to specialty training had reached equality at: 49.48% and 50.53%, respectively. Twenty-four years later, in 2015, those percentages were 34.31% and 65.69%. These figures illustrate the clear process of the feminization of the Spanish medical workforce.

If ability, skills and preferences were identically distributed between sexes, male and female doctors would be evenly distributed across specialties leading to an egalitarian allocation of individuals. The latter is a priority goal of most societies, especially in activities fully funded by taxpayers. Nonetheless, in the Spanish resident market the large increase in the number of women has not been translated to an equal representation of them in each specialty. Whilst specialties like internal medicine, general practice and psychiatry consistently show an equal representation of both sexes over time, some others have not, and have become either female-dominated or male-dominated specialties. A good example is surgical training posts, that are always in high demand among medical students, and have persistently shown an over-representation of male junior doctors.[23] The gender gap has not vanished, and

[23]In this chapter we often use the term male-dominated surgical specialties and it should be noted that we refer to the group of surgical and medical-surgical specialties that over the years have shown an over-representation of male doctors. See Tables 4.1 and 4.2 for a more detailed classification of the

in some cases, such as plastic surgery, has even widened with the feminisation of the more recent cohorts of medical trainees.

Figure 4.1 shows the distribution of first year male doctors in training across specialties, for the years 1991 and 2014, relative to the total proportion of men choosing a specialty in the given year.[24] Gender balanced specialties are those that lie on (or near) the value one represented by a horizontal red line. We would have expected a more gender balanced distribution of doctors across specialties in 2014 than in 1991, due to the feminization of the profession; however, the two graphs look quite similar and we even observe a greater dispersion in 2014. For example, the proportion of men entering plastic surgery in 1991, dot number 14 in Figure 4.1, was approximately 1.7 times larger than the proportion of men choosing specialty that year. That proportion increases to 2.4 times in 2014. Figure A2.1, in Appendix Section 6.2, shows the distribution of first-year doctors across the 47 specialties for the period 1991 to 2014. There are 47 figures, one for each specialty, and each of them consists of two lines for each gender. The blue solid (red dashed) line represents the percentage of men (women) from the total selecting a specialty that given year, whilst the green dotted (yellow dashed) line shows the percentage of men (women) choosing that particular specialty. Internal medicine, subfigure (aa), and psychiatry, subfigure (ar), are good examples of gender balanced specialties where we observe that the two described lines overlap for both men and women.

This chapter aims to disentangle the origin and causes of the persistent gender gap in surgical specialties in the Spanish resident market. In Chapter 2 we establish that gender occupational segregation is present for the new cohorts of UK junior doctors in specialty training and discuss some of the possible drivers of the observed segregation. In this chapter we explore two of them. First we analyse the role of social interactions in shaping doctors' decisions to specialize. According to Manski (1993a) a person can emulate someone with a similar history or use role models to forecast his or her

specialties.

[24]Each dot results from the quotient of the proportion of male doctors choosing specialty j in year t by the proportion of doctors choosing a specialty in year t. For example in 2014, 32.1% of the total number doctors choosing specialty were men whilst 67.9% were women. A ratio equal to one indicates that specialty j is gender balanced, whilst a ratio smaller (larger) that one indicates that male doctors are under-represented (over-represented) with respect to their representation in the population of doctors choosing specialty in year t.

own future behaviour conditional on choosing a given action today. Following that argument, in this chapter, we test whether being exposed to female role models, i.e. female junior doctors in surgical male-dominated specialties, increases the probability of females choosing a male-dominated surgical specialty, other things equal. The second question addresses the role of the current Spanish specialty allocation system in perpetuating the observed unbalanced specialty outcomes. For that purpose, we quantify the effect of a change in the allocation system that took place in the year 2010, which increased the competitiveness of the process, and test whether it has affected men and women differently, specifically whether it has disadvantaged women.

There are several undesired consequences associated with occupational segregation. These include earnings disparity, shortages of specialists, lower quality of care and a lower quality of working experience. The following paragraphs set those out in detail.

Arcidiacono and Nicholson (2005) found, for the United States medical market, that the large male-female gap in physician earnings is due in large part to specialty choice, since women are more likely to choose low paying specialties such as general practice. On average, according to OECD Indicators (2015), in Spain a general practitioner with 20 years experience has a salary[25] of €56,495, whilst a specialist with the same experience earns approximately €8000 more.[26] In 2015 the percentage of women choosing a post in general practice was 73%, approximately 7.31% more than the total percentage of women choosing a specialty that year, 65.69%. Spanish doctors seem to form fairly accurate income expectations before choosing a specialty. Harris et al. (2014) shows the estimated valuation of seven different attributes of all specialties extracted from a survey administered to 978 final-year medical students in Spain. Students attributed a mean annual remuneration of €105,375 and €97,160 to male-dominated and non male-dominated surgical specialties, respectively.[27] The figure is €56,000 for general practice. The discrepancies between OECD figures and doctors' valuations are linked to the fact that in the national Spanish health system private practice income is considered a superior proxy for earnings (Harris et al. 2013) and

[25] In Spain, doctors' salary is a function of seniority in the job, region of practice and number of days the doctor is on duty.

[26] The reported figures do not include any private practice income.

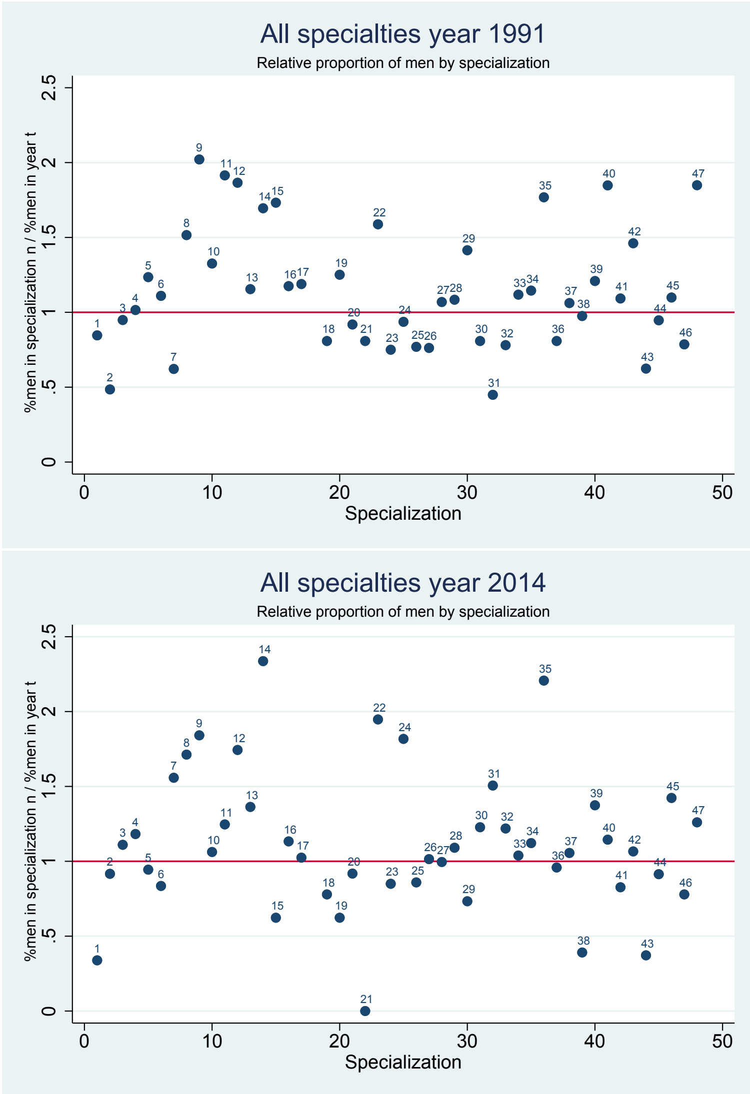
[27] See Table 4.2 for the classification of surgical and medical-surgical specialties into male-dominated and gender-balanced.

although there is no published national representative data by region and specialty on the earnings of Spanish doctors, medical students may have incorporated the private practice earnings into their income expectations. Harris et al. (2014) show medical students' estimated joint valuations of lifestyle and working hours; on a scale of one to ten, where ten represents the highest valuation, those are 5.71, 6.51 and 7.76 for male-dominated, non-male-dominated surgical specialties, and general practice, respectively. Medical students perceive a trade-off between income and the ability to reconcile work with family and leisure, and it seems that women in particular are less likely to choose specialties with a less favourable valuation of the attribute lifestyle and working hours (Harris et al. 2014).

In addition, Arrizabalaga et al. (2015) found evidence of the existence of the *leaky pipeline phenomenon*. The authors analysed data from a top hospital in Spain over a 13-year period, finding that despite the achievement of a 50% representation of female doctors in training, women showed a lower probability of internal promotion and that, in comparison to male doctors with similar years of experience, they tended to progress later into promoted posts. According to Bettinger and Long (2005), under-representation of women in certain areas may contribute to future shortages in critical fields. This seems a plausible scenario in the highly feminized Spanish medical workforce.

Both under-representation and unequal distribution across specialties and hierarchal positions might be problematic as there is evidence of dissimilarities in the way that men and women practice medicine. Bloor et al. (2008) find that male doctors in the UK have significantly higher activity rates than females, even after accounting for patients' case mix. By contrast, several papers in the medical literature have found that female doctors provide higher quality care than men. Tsugawa, Jena, Figueroa et al. (2017) found for the United States that differences in practice patterns between male and female internists lead to lower readmission and mortality rates of the patients treated by the latter group. Wallis et al. (2017) find similar mortality results on elective procedures performed by female surgeons in Canada. Baumhäkel et al. (2009) found that females are more likely to adhere to clinical guidelines and Lurie et al. (1993) show that female doctors provide preventive care more often than male doctors. Irrespective of the causes of the differences in patient outcomes and

Figure 4.1: Distribution of male junior doctors across specializations for years 1991 and 2014



1 Allergy; 2 Clinical Analysis; 3 Anatomical Pathology; 4 Anaesthetics; 5 Vascular Surgery; 6 Gastroenterology; 7 Clinical Biochemistry; 8 Cardiology; 9 Cardiovascular Surgery; 10 General Surgery; 11 Oral Surgery; 12 Orthopaedic Surgery; 13 Paediatric Surgery; 14 Plastic Surgery; 15 Thoracic Surgery; 16 Dermatological Surgery; 17 Endocrinology & Diabetes; 18 Pharmaceutical Medicine; 19 Geriatric; 20 Haematology; 21 Medical Hydrology; 22 Immunology; 23 Occupational Medicine; 24 Sport and Exercise Medicine ; 25 General Practice; 26 Rehabilitation Medicine; 27 Intensive Care Medicine; 28 General Internal Medicine; 29 Legal and Forensic Medicine; 30 Nuclear Medicine; 31 Public Health; 32 Microbiology; 33 Renal medicine; 34 Respiratory; 35 Neurosurgery; 36 Clinical Neurophysiology; 37 Neurology; 38 Obstetrics & Gynaecology; 39 Ophthalmology; 40 Medical Oncology; 41 Clinical Oncology; 42 Otolaryngology; 43 Paediatrics; 44 Psychiatry; 45 Radiology; 46 Rheumatology; 47 Genito-Urinary Medicine

style of practice, these results suggest that there might be potential gains in increasing the representativeness of females in some specialties. A gender balanced workforce might lead to positive externalities since both men and women could learn from each other. Finally, male-dominated specialties, as shown by Harris et al. (2014), are associated with a worse work-leisure balance than the other specialties. Increasing the proportion of female doctors could lead to the creation of lobbies and unions to appeal for better policies to aim at achieving a better work-leisure-family balance.

The remainder of the chapter is organized as follows: Section 4.2 describes in detail the operation of the Spanish allocation system. Section 4.3 addresses estimation of the role model effect on the doctors' decisions to specialize. Section 4.4 covers the analysis of the change in the allocation system and tests whether the change has affected male and female doctors differently. Section 4.5 jointly discusses the findings of the two research questions and draws a conclusion. Tables are in Section 4.6.

4.2 The Spanish medical specialty allocation process

The Spanish Health System (Sistema Nacional de Salud) is dominated by the public sector, which accounts for 70% of total expenditure on health care, and is mainly funded through taxation. Undergraduate medical education in Spain is offered by 31 public universities and 9 private universities and has a duration of 6 years. During that time, medical students take modules in basic, social and clinical sciences, and in the fundamental principles of medicine. In the third year medical students start their clinical training in university hospitals and primary care centres. For three years students rotate in different services, including surgeries, medical specialties, and general practice. During the rotations medical students are under the supervision of consultants and junior doctors. From this contact students can learn about the characteristics of the specialties, such as the type of work involved, workload, the doctor-patient relationship and form income expectations. Medical students can also arrange informal clerkships if they are interested in gaining further experience in a specialty. Experiences, mentors and colleagues that students have during the clinical training period will influence their preferences for the various specialties (Coleman 1966; Arcidiacono and Nicholson 2005).

After completion of undergraduate medical studies, newly graduated doctors need to gain access to one of the 47 postgraduate specialties available in the Spanish Health System. Following Torres et al. (2008) we classify these in four core groups: *medical*, *laboratory*, *surgical* and *medical-surgical*. The duration of training is different, for most *medical* and *laboratory* specialties it lasts four years, whilst for *surgical* and *medical-surgical* it lasts five years. Table 4.1 sets out the detailed classification.

The allocation process of specialist training positions in Spain is widely known as MIR ('Médico Interno Residente') and literally means 'resident medical intern'. It is organized and regulated centrally by the Ministry of Health (Harris et al. 2017). It is a one-sided sequential allocation mechanism, where individuals self-select themselves into specialties and the latter play a passive role (Harris et al. 2014). The number of available training positions varies from year to year and since 2006 is between 6,000 and 7,000, from which one quarter belong to general practice.

All doctors who hold an undergraduate medical degree and who have successfully completed the MIR state examination in a given year can take part in the allocation process for that year. The MIR examination is a multiple-choice test and takes place at a national level on the same day and at the same time in different locations across Spain. The multiple-choice test rewards correct answers with three points and penalizes incorrect answers with minus one point. Since the allocation process is sequential, doctors choose their preferred training programme according to their position in a pre-established ranking. The ranking order is a function of doctors' grade point average in their medical undergraduate studies (GPA) that has a contribution of 10% to the total score and their score on the MIR examination, which constitutes 90% of the total score. Doctors for whom there is no suitable alternative can opt out of the process that year and opt for a position in future calls, for which they will need to re-take the state examination.

4.3 Question 1: Do female role models affect doctors' decisions to specialize?

A standard explanation from economic theory for the occupational gender gap is the existence of intrinsic differences in preferences between men and women. From a traditional economics perspective preferences are not affected by the social environment and there is scepticism about the estimation of social interactions, mainly due to the difficulty of separately measuring the social effect from other confounders (Arcidiacono and Nicholson 2005). Nonetheless, the lack of surgical role models has been highlighted as a detractor in recruiting more women to the field and the fact that surgical specialties have been seen as a *man's job* for a long time has been perceived as an entry barrier by some women (Fitzgerald et al. 2013). It is therefore possible that observed differences in preferences might be due to the existence of information phenomena such as emulation, mentoring or role model effects (Manski 1993a; Chung 2000).

Manski (1993b) and Manski (2000) classify social interactions in three categories: *endogenous*, *exogenous* and *correlated* effects. *Endogenous* effects refer to the propensity of medical students to vary their behaviour towards specialty choices with the behaviour of the group; *exogenous* effects refer to the variance in behaviour that responds to exogenous characteristics of the group (e.g. quality of medical schools, degree of accessibility to mentors, degree of commitment of faculty); and *correlated* effects refer to the situation where similar medical students behave similarly because they share similar characteristics or face the same institutional framework. The specialty choice decisions in the Spanish resident market may be influenced by a mix of these three effects.

The identification of *endogenous* social effects is challenging and leads to what has been termed the *reflection* problem. Manski (1993b) describes it as the problem that arises when, following the observation of the distribution of behaviour in a population, a researcher tries to infer whether the average behaviour in some group influences the behaviour of the individuals that comprise the group. We, therefore, focus on the identification of *exogenous* effects and from within the wide range of these we estimate the effect of informational role models in shaping medical students specialty choices. According to Manski (1993a), individuals obtain much of their information by observing the decisions and the outcomes realized by *others*. In reality, the definition of *others* varies from individual to individual: it can be from one person, a very enthusiastic lecturer, to a combination of people and situations, as when attending a medical school where the majority of students have an interest in surgical specialties. Examples of influential figures can be lecturers at medical school, medical consultants and junior doctors in university hospitals, alumni and even classmates.

We develop a framework for evaluating the effect of close female role models in doctors' decisions to specialize. In particular, and justified by the occupational segregation described in the introduction, we focus our analysis on *surgical* and *medical-surgical* specialties and we test whether female junior doctors in training in those specialties are seen as role models by (female) medical students. We test whether being exposed to a larger proportion of female doctors in an otherwise male dominated specialty increases the probability of a female doctor choosing that specialty. For that purpose, we use information from a cross-sectional survey (the MIR Survey) where students have been asked about their preferred specialty, i.e. stated preferences, if all the specialties were available in their choice set.[28]

The MIR Survey has been previously used by Harris et al. (2013) to measure the impact of the Great Recession that started in 2008 on the specialty choices of doctors and by Harris et al. (2014), in a paper that simulates the outcomes of different specialty allocation systems, to evaluate alternative policies to the current system. This second paper aims to address the shortage in general practice in the Spanish resident market. A further paper, Harris et al. (2017) seeks to analyse medical student preferences on residency programmes under two different choice scenarios: one being the actual specialty chosen and the other being the programme the student would have chosen if all residency programmes were available, defining the latter as the *counterfactual choice*. The authors find that preferences are not intrinsically stable but depend on the context of the choice being made,[29] contradicting the traditional view

[28]As described in Section 4.2 the specialty allocation process is sequential and therefore only the doctor ranked in the first position will have all training posts in her choice set. The analysis of revealed choices from the allocation process will fail to capture the effect of female role models, as most of the bottom ranked doctors do not have the highly competitive surgical specialties in their choice set.

[29]Harris et al. (2017) find that doctors' preferences depend not only on the choice set available, but also on the choices made by others, in particular of those at the top of the ranking.

on intrinsic preferences. In this chapter, as in Harris et al. (2017), we test the role of social interactions on the *counterfactual* specialty choices instead of the actual choices, since the latter are constrained by the choice set available at the moment the student makes her choice.

The existing literature analysing role model effect on occupational choices is not extensive and has found mixed results. Bettinger and Long (2005) estimated how having a female faculty member in a course affects the likelihood that a female student would take additional credit hours in a particular subject. Their results support the role-model effect for some disciplines such as geology, mathematics and statistics, but they fail to find positive and significant effects in some male dominated fields such as engineering and physics. Rothstein (1995) studied whether the percentage of female faculty had an influence on female student' post-graduate educational and labour market outcomes; finding that a higher percentage of female faculty increases the probability of attaining a higher degree, however it has no impact on the labour market earnings. Neumark and Gardecki (1996) studied whether female Ph.D. students having female dissertation chairs resulted in more successful outcomes for them. They found that there was no effect on labour market outcomes, however with respect to time and completion rate, they found beneficial effects of the presence of female faculty members. For medical students, Arcidiacono and Nicholson (2005) estimated the impact of peer effects in medical school on the achievement and specialty choices of medical students. They found evidence of a positive peer effect for female students in examination scores, however no effect was found in terms of specialty preferences after controlling for medical school fixed effects.

4.3.1 Data

We use two different data sources: the MIR Registry that contains the information we use to create the role model variable and MIR Survey that we use to test the existence of the role model effect. In the sections below and in Table 4.3, we describe the particularities of both datasets.

4.3.1.1 MIR Registry

The MIR Registry is a cross-sectional dataset for the years 2003 to 2015 (N= 73,787) and comes from doctors' administrative records held by the Spanish Ministry of Health. The MIR Registry includes a record of doctors' actual choices of specialty and training hospital. Table 4.1 shows the list of specialties classified in the four core groups and Table 4.2 classifies surgical and medical surgical specialties into male-dominated and gender-balanced. The latter classification is based on historical ratios. We classify specialties for which the intake of female residents has been smaller than 50% for all the years since 1991 as male-dominated or as gender-balanced otherwise (see Figure A2.1).

The MIR Registry includes the doctor's original *Ranking Position* in the MIR process, the *Specialty Chosen*, the *Training Location* and the *Year* the doctor participates in the allocation process. The variable *Women* takes value one if the doctor is female and zero otherwise. The variable *Spanish* takes value one when the doctors' nationality is Spanish and zero otherwise. The variable *Age*, defined as an integer, indicates the age of the doctor during the specialty allocation process. The *Medical School* attended is also available and we include a dummy indicator for each of the 34 Spanish medical schools.[30] The MIR Registry also includes the Grade Point Average, *GPA*, of medical undergraduate studies that is continuous and ranges from 1 to 5, and is only available for the most recent years. The variable *Exam Score (ES)* provides the results of the state examination. This variable takes only integers and has an upper limit equal to 675. We utilise the variables *Specialty Chosen*, *Training Location* and *Women* from the MIR Registry to construct the role model variable. Section 4.3.2 describes the construction of the role model variable in detail.

4.3.1.2 MIR Survey

The second data source we employ is a cross-sectional survey, MIR Survey, that is sent to doctors every year after the specialty allocation process has taken place. In this chapter, we analyse three waves of the MIR Survey for the years 2013, 2014 and

[30]In section 2, 40 medical schools are mentioned; however, those of recent creation are not included in our data as it would take more than six years for the first cohort of doctors to take part in the MIR process

2015 (N= 8,739). The response rate of the MIR Survey is similar across years and is approximately 50% of the total number of doctors choosing specialties in a given year (Harris et al. 2014). More detailed information about the survey design can be also found in Harris et al. (2014).

The survey includes information on stated preferences of a doctor's decision to specialize. Doctors are asked about their preferred specialty and that information is captured by the variable *Preferred Specialty*; these preferences are unconditional to their ranking position and therefore might be different from the revealed preferences, given by variable *Specialty Chosen*, that comes from the MIR Registry. We classify the *Preferred Specialty* into the four core groups described in Table 4.1: *medical*, *laboratory*, *surgical* and *medical-surgical*. The two latter constitute our groups of interest and therefore we further classify the specialties from those two groups into male-dominated and gender balanced (see Table 4.2).

The MIR Survey includes the same demographic and academic variables present in the MIR Registry and we use them as control variables. It also includes the variable *First MIR*, that takes value one if the doctor is participating in the MIR allocation process for the first time and zero otherwise.

4.3.2 The role model effect

In this section, we present the construction of the role model variable. Then we describe the model, the assumptions, the estimation technique and the limitations of our approach.

4.3.2.1 The role model variable

To construct the treatment variable that captures the magnitude of the social interaction of interest we focus on the three-year period during which undergraduate medical students complete their clinical training (see section 4.2). Medical schools in Spain have agreements with university hospitals that provide undergraduate clinical training and postgraduate specialty training. Medical schools can have agreements with one or more hospitals. We define role models as female junior doctors in postgraduate training in university hospitals. We assume that all undergraduate students who attended the same medical school at the same time are exposed to the same group of junior doctors. Using the variables *Specialty Chosen*, *Training Location*, *Year* and *Women* from the MIR Registry, we identify female junior doctors across specialties, university hospitals and years. Table 4.4 illustrates, with an example, how we connect undergraduate medical students and female role models for those students who started medical school in the academic year 2006/07.

To construct the role mode variable, we need to define the notation for the framework to be analysed. We have doctors choosing specialties represented by $i \in I = \{i \in \mathbb{N} : 1 \leq i \leq \bar{I}\}$, a set of specialties represented by $j \in J = \{j \in \mathbb{N} : 1 \leq j \leq \bar{J}\}$, training hospitals by $h \in H = \{h \in \mathbb{N} : 1 \leq h \leq \bar{H}\}$ and years represented by $t \in T = \{t \in \mathbb{N} : 1 \leq t \leq \bar{T}\}$.

The first step in the construction of the role model variable is the creation of a dummy indicator, $womanyes_{htj}$, that takes value zero if there is no female junior doctor in postgraduate training in hospital h, year t and specialty j. The variable takes value one if *there is at least one* female doctor in training in hospital h, year t and specialty j. The idea behind this extreme classification it is to identify medical students who were exposed to no or very few females during their undergraduate clinical training. Secondly, for each training hospital, h, we take average of the variable $womanyes_{hjt}$ for the group of specialties classified as *male-dominated* (see Table 4.2 for the full list), as given by expression (4.1).

$$\overline{womenyes}_{h,t} = \frac{\sum_{j=1}^{J} womenyes_{htj}}{J} \tag{4.1}$$

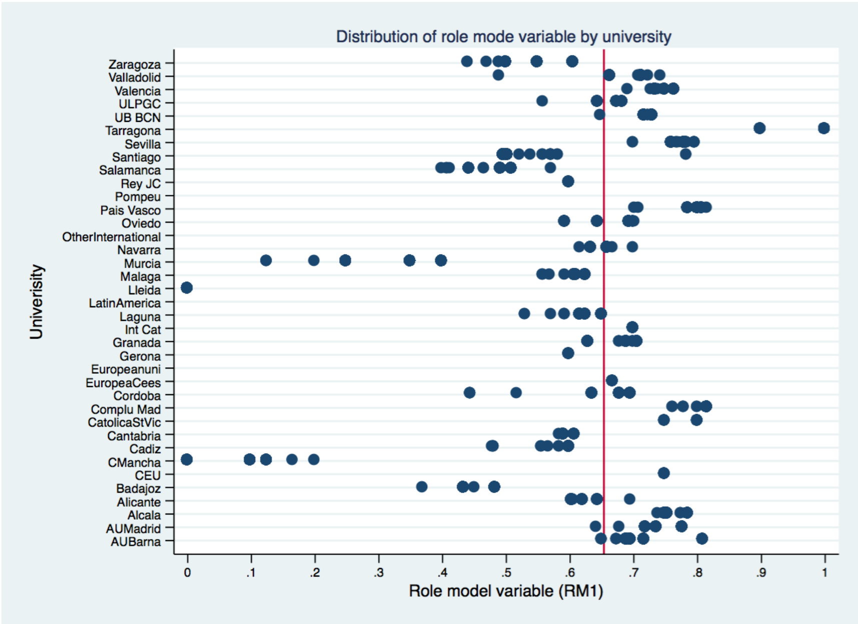
Then for each medical student i we compute the role model treatment variable, denoted by $RM1$, by calculating the average of the variable $\overline{womenyes}_{h,t}$ over the number of the years of undergraduate clinical training, as given by (4.2).

$$RM1_i = \frac{\sum_{t=1}^{T} \overline{womenyes}_{h,t}}{T} \tag{4.2}$$

The resulting variable $RM1_i \in [0, 1]$ captures the exposure of medical students to female role models in male dominated surgical specialties during the years of undergraduate clinical training. The variable ranges from zero, indicating that the medical student has not been exposed to a role model in any of the clinical training years, to 1, indicating that every year there was at least one female role model present.

The treatment variable can also be interpreted as the probability of being exposed to at least one female junior doctor over the years of clinical training.

Figure 4.2: Distribution of role model variable by university



Red line indicates average value of the role model variable ($\overline{RM1} = 0.653$)

The role model treatment variable has a number of limitations. First, whilst we have information about female role models for each university hospital h, where there is more than one h associated with a medical school we need to take averages of the $RM1$ for all of them,[31] as we do not know which one the student completed their undergraduate clinical training in, and we are not able to link medical students to unique training hospitals. Nonetheless, in the majority of cases, medical students rotate in the different training hospitals to receive clinical training for different specialties and therefore can be directly or indirectly exposed to female role models from all the training hospitals associated with a medical school. Second, we can only compute the role model variable for those students for which we know the year they finished their medical studies. Third, there is no information in our data for those doctors who

[31]In that case the role model variable will be given by:

$$RM1_i = \frac{\sum_{h=1}^{H} \frac{\sum_{t=1}^{T} \overline{womenyes}_{h,t}}{T}}{H}$$

completed their medical undergraduate studies outside of Spain. In 2013, 2014 and 2015 foreign qualified doctors constituted 25%, 19% and 13% respectively of the total number of doctors taking part in the MIR process. Due to the mentioned limitations we can only compute the role model treatment variable for 71.6% of the respondents of the MIR Survey, which translates to a sample size of N=6,261. Figure 4.2 shows the distribution of $RM1$ by medical school, where each dot represents the value of $RM1$ for doctors who carry out their specialty training at different time periods.

4.3.2.2 Econometric model and estimation strategy

We define three outcome variables denoted by y_n where $n = 1, 2, 3$. Table 4.5 sets out these in detail. These variables result from three different groupings of the *Preferred Specialty* that is extracted from the MIR Survey. Although, ideally we would like to estimate the role model effect for each specialty separately, i.e. to compute a role model treatment variable for each specialty, the survey exhibits a small sample size that impedes this approach. Hence, we need to group similar specialties together and we show the estimates for three different groupings. The variable y_1 is a dummy that takes value one if the individual indicates a preference for any male-dominated *surgical* or *medical-surgical* specialty[32] and value zero if the individual indicates a desire for any other option, i.e. any *medical*, gender-balanced *medical-surgical* and *surgical*, or *laboratory* specialty. Variable y_2, takes value one if the doctor chooses any *surgical* option, both male-dominated and gender-balanced, and zero if the individual has chosen any other specialty, i.e. *medical* or *laboratory*. For variable y_3, we restrict the analysis to the subsample of doctors that have a declared interest in surgery and test whether a greater exposure to the treatment variable, $RM1$, increases their probability of choosing a male-dominated surgical specialty relative to a gender-balanced surgical specialty.[33] Hence, y_3 takes value one if an individual chooses a male-dominated *surgical* or *medical-surgical* specialty and zero if a gender-balanced *surgical* specialty is chosen instead.

For each medical student i we observe $y_{ni} = 1$ or $y_{ni} = 0$, mutually exclusive binary

[32] See Table 4.2

[33] Another justification of the sample restriction is the difference in length of training between (1) *medical* and *laboratory* and (2) *surgical* and *medical-surgical* specialties. The majority of specialties in the first group require four years of training compared with five years for the second group.

outcomes, and we estimate the effect and significance of the role model variable on the probability of observing $y_{ni} = 1$ by means of a Probit regression. For that purpose, we define an underlying continuous latent variable y_n^*, that satisfies equation (4.3) and is related to the outcome variable y_n through equation (4.4).

$$y_{ni}^* = \beta_{n0} + \beta_{n1} RM1_i + X_i' \beta_n + \varepsilon_{ni} \quad n = 1, 2, 3 \tag{4.3}$$

$$y_{ni} = \begin{cases} 1\, if \quad y_{ni}^* > 0 \\ 0\, if \quad y_{ni}^* < 0 \end{cases} \tag{4.4}$$

In equation (4.3) the role model treatment effect is represented by $RM1$. The vector X' encompasses the group of control variables that we classify as demographic, such as *Women*, *Age* and *Spanish* and academic covariates that include *GPA*, *First MIR* and *Medical School* dummies. When we include the medical school fixed effects, since individuals that attended the same medical school during the same period have the same values of $RM1$, we need to rely on the time variation of the treatment variable to ensure identification.

In expression (4.3), ε_i refers to the error term that we assume is identically distributed following a normal distribution. However, we relax the usual requirement that observations need to be independent by clustering the standard errors and allowing for intra-group correlation. The group choice corresponds to the year doctors made their specialty choices and responded to the MIR Survey (i.e. 2013, 2014 or 2015). Survey respondents from different years are extracted from different populations, as they sat a different MIR examination and might have faced a different social context.[34]

$$p_{ni} \equiv Pr(y_{ni} = 1|X) = \Phi(\beta_{n0} + \beta_{n1} RM1_i + X_i' \beta_n) \quad n = 1, 2, 3 \tag{4.5}$$

Expression (4.5) shows the regression model that is formed by parametrizing p_{ni} to depend on an index function $\Phi(\beta_{n0} + \beta_{n1} RM1_i + X_i' \beta_n)$ where β is a vector of unknown parameters and $\Phi(.)$ is the cumulative distribution function of the Probit distribution and ensures that $0 \leq p_{ni} \leq 1$. Given a correct specification of the $\Phi(.)$ the

[34] Harris et al. (2013) found evidence of medical students in Spain changing their preferred specialty to specialties with more certain job prospects after the start of the Great Recession in 2008.

maximum likelihood estimators of expression (4.5) produce consistent estimators.

The estimated parameters from the Probit model do not have a straightforward interpretation as, unlike the linear regression model, its estimates are not equivalent to the marginal effect of a covariate in the estimated probability. The marginal effect in the Probit model is given by (4.6) where $\phi_i(X_i'\beta_n)$ is the probability distribution function associated with $\Phi(.)$. As the marginal effect of one covariate depends on all the parameters and on the actual values of the vector of covariates we compute instead the average marginal effect (*AME*). The *AME* is computed for the average value of all the explanatory variables ($\bar{X}_i$) including X_k.

$$\frac{\partial P\left[y_{ni}|X_i\right]}{\partial X_{k_i}} = \frac{\partial \Phi(X_i'\beta_n)}{\partial X_{k_i}} = \phi_i(X_i'\beta_n) * \beta_{nk} \tag{4.6}$$

4.3.3 Results

4.3.3.1 Descriptive statistics

Table 4.6 shows descriptive statistics for the complete MIR Survey and the reduced sample for which we can compute the role model variable $RM1$. The two samples exhibit differences, as the role model sample presents a higher proportion of females (71.8% vs. 67.8%), Spanish (98.7% vs. 86%) and younger doctors (mean age 25.35 years vs. 27.04). The doctors from the role model sample also present on average a higher *GPA* (1.96 vs. 1.94) and MIR Exam score (404.92 vs. 390.53). The reported *Preferred Specialty* classified in the four core groups present similar means for the two samples. The percentages for complete MIR survey and reduced role model sample are 6.4% vs. 4.6% for laboratory, 25.7% vs. 25.7% for medical-surgical, 57.8% vs. 60% for medical and 10% vs. 9.8% for surgical specialties. The role model sample over-samples female and younger doctors as the majority of foreign qualified doctors are men and older than the Spanish qualified doctors. Female doctors are the target group of the analysis, therefore a greater representation of them provides further validation of role model estimation results.

Table 4.6 also shows a comparison between *Preferred Specialty* and *Specialty Chosen*. In some cases, especially for those individuals at the top of the ranking distribution, the chosen specialty and the desired one coincide, however in the majority of cases the two differ. We observe how *surgical* and *medical-surgical* specialties are oversubscribed as the percentage of doctors declaring preference for those options is considerably larger than the percentage of doctors who actually choose them. The percentages are 9.8 versus 6.5 for *surgical* specialties and 25.7 versus 16.6 for *medical-surgical* specialties in the role model sample. Finally, the descriptive statistics for the role model sample show that 20.3% of doctors indicated a male-dominated surgical specialty as their preferred choice (variable y_1) whilst 35.4% indicated a preference for any type of surgical specialty (variable y_2). In the reduced sample of doctors who expressed an interest for a surgical specialty 43.7% of them indicated a male-dominated surgical specialty as their preferred choice with respect any other gender-balanced surgical specialty (variable y_3).

4.3.3.2 Estimation results

Table 4.7, Table 4.8 and Table 4.9 display the estimation results for y_1, y_2 and y_3 respectively. In each table we report the results for four different specifications that differ from each other in the number of covariates included in the estimation. Specifications (1) and (2) present the estimation results for the complete sample being the only difference that (1) does not include the treatment variable $RM1$ and (2) does. Specifications (3) and (4) include all the covariates but differ in the sample used, (3) presents the estimation results for the sample that includes only men and (4) for the sample that includes only women. For each specification, (1)-(4) we present two columns of results: the Probit estimates of the vector of unknown parameters represented by β in equation (4.3) and the average marginal effects (AME) of each explicative covariate.

Estimation results for y_1

Table 4.7 shows the estimation results for the dependent variable y_1. The estimates associated with $RM1$ in specifications (2) with N=6,181, (3) with N=1,745 and (4) with N=4,438 are all positive and statistically significant at the 99% confidence level. The role model effect seems to be larger for the men-only sample than for the female-only sample. A standard deviation increase in the treatment variable $RM1$ (0.161) augments the probability of choosing a male-dominated surgical specialty by

0.034, 0.059 and 0.026 for the complete, male and female sample respectively.

The observed estimates for the variables *Women* and *Age* exhibit the expected sign as both are negative and significant at the 99% confidence level. Looking at the estimates of specification (2) the associated marginal effect indicates that,other things equal, being a female doctor decreases the probability of choosing a male-dominated surgical specialty by 0.093, with respect to any other specialty. Similarly, for each year older a doctor is, the probability of $y_1 = 1$ decreases by 0.005. The variable *First MIR* is also negative and statistically significant at the 99% confidence level. This implies that doctors taking the examination for the first time are less likely to choose a highly competitive male-dominated *surgical* specialty and the marginal effect is -0.054. No significant effects were found for the variables *Spanish* or *GPA*. The results for *Medical School*, where Universidad Autonoma de Barcelona[35] is the omitted category, are mixed and most of them non-significant. The comparison of specifications (1) and (2) show that estimates for *Medical School* present little variation after the inclusion of $RM1$ with the exception of some like *Castilla La Mancha* or *Murcia* that are the medical schools with less observations in our sample. In addition the estimates for specifications (3) and (4), in some cases, present different signs and magnitudes for men and women, a result that can be partially explained by the differences in sample sizes.

Estimation results for y_2

Table 4.8 shows the estimation results for y_2, where $y_2 = 1$ indicates the individual chose a *surgical* specialty whilst $y_2 = 0$ indicates the election of any other non-surgical specialty. For y_2, the estimates of $RM1$ are positive for all specifications, however only statistically significant at the 90% confidence level for specification (3). A standard deviation increase in $RM1$ (0.161) augments the probability of choosing a surgical specialty by 0.083, but only for male doctors. No significant results were found for the female sample.

The estimates for the complete sample (N=6,183), including the role model variable,

[35] The choice of omitted category is arbitrary. However, for interpretability purposes it should be noticed that Universidad Autonoma de Barcelona is often classified as one of the top universities in the country in the field of Medicine (Universidad Autonoma de Barcelona 2017)

are shown by specification (2). Results for the variable *Women* exhibit a similar sign to those observed in Table 4.7, however of a smaller magnitude (-0.037 vs. -0.093) and only significant at the 95% confidence level, whereas, the magnitude of the effect for *Age* is larger and implies that being a year older decreases the probability of choosing a surgical specialty by 0.011 (significant at the 99% confidence level). The variable *GPA* is statistically significant for the general and men only samples, specifications (2) and (3), suggesting that (male) doctors with a higher *GPA* are more likely to choose a surgical specialty over any other non-surgical option. As for y_1, the variable *First MIR* presents negative and significant coefficients, the magnitude of the effect being larger for men than women (-0.148 vs. -0.116). Finally, the effects of *Medical School* are less relevant, i.e. fewer medical school indicators are significant, in the estimation of y_2 than they were for y_1.

Estimation results for y_3

Table 4.9 shows the results for y_3 where $y_3 = 1$ indicates that the doctor's preferred option is a male-dominated specialty and $y_3 = 0$ that it is a gender-balanced *surgical* specialty (see Table 4.2). In this case, the sample size is reduced to N= 2,186 as we restrict the sample to the individuals who expressed an interest for surgical specialties only.

The estimates of the role model variable, $RM1$, for the different specifications display mixed results and we only find significant estimates for specification (4), the women only sample. We observe that an increase of one standard deviation in the exposure to female role models increases the probability of choosing a *male-dominated surgical* specialty by approximately 0.050 for female doctors.

Specifications (1) and (2) show the results for the complete sample, the only difference between the two being the inclusion of the variable $RM1$. We observe a negative and statistically significant effect of the variables *Women* and *First MIR*, both statistically significant at the 99% confidence level. Being a female doctor decreases the probability of choosing a *male-dominated surgical* specialty by -0.231, ceteris paribus. Similarly, doctors taking the MIR examination for the first time are less likely to choose a male-dominated surgical specialty than a gender-balanced surgical specialty, this AME is equal to -0.028. As for y_1 and y_2, the estimates associated with

Medical School dummies are mixed, in some cases they present different signs for men and women and larger standard errors due to the significant reduction of the sample size with respect to y_1 and y_2 .

4.3.4 Discussion

The aim of the first part of the chapter has been the analysis of whether social interactions can serve as a vehicle for tackling the gender imbalance in male-dominated surgical specialties. The estimation results for the effect of female role models are positive and statistically significant for both male and female doctors. Unexpectedly, the effect seems to be of a larger magnitude for male doctors and suggest that female surgeons are also perceived as positive role models by male doctors. However, it also signals that $RM1$ might be capturing other elements from the undergraduate clinical training environment. If clinical environments with larger values of $RM1$ are perceived as more attractive, then they will attract a larger proportion of females as well as a larger proportion of males. Therefore, $RM1$ will not only be capturing the effect of informational role models but also some other exogenous characteristics affecting all medical students that participated in the same clinical training programme.

The results for the reduced sample of doctors who only expressed an interest for a surgical specialty, outcome variable y_3, show a positive and statistically significant effect of $RM1$ for female doctors on the probability of choosing a male-dominated specialty. The effect for the sample of men only is negative, however not statistically significant. Therefore, in this reduced group of doctors, a higher exposure to female role models increases the probability of women choosing a male-dominated instead of gender-balanced surgical specialty. This sample is more homogeneous as it only includes doctors with stated preferences for surgical or medical surgical specialties and within that group; female role models have a positive attraction effect for women whilst the effect is not statistically significant for men.

In general and for the three outcome variables, we find that male and younger doctors are more likely to choose a male-dominated surgical specialty. These results are consistent with the findings of Chapter 3 regarding the application patterns of the UK with respect to surgical specialties. We also find that individuals participating in the MIR process for the first time are less likely to declare male-dominated surgical specialties as their preferred choice. Doctors opting for (and finally getting into) a highly competitive male-dominated specialty are more likely to need to re-take the MIR examination. The latter has some high opportunity costs associated with it; these include monetary costs, such as the lost earnings connected to the one-year delayed entry to the job market and the costs of examination preparation, and non-pecuniary costs, such as the possible health problems associated with the stress and anxiety caused by the examination preparation. Although, we do not have data on doctors' socioeconomic backgrounds, we conjecture that those from privileged backgrounds will be more likely to re-take the examination as they are also more likely to be able to afford the opportunity cost of re-taking it.

Our focus on surgical specialties does not imply that there are not other significant gender imbalances in the Spanish resident market. As Figure A2.1 shows, other specialties, such as obstetrics and gynaecology (subfigure (al)) or paediatrics (subfigure (aq)), display an over-representation of female doctors. The main difference between the latter and the group of specialties we analysed in this chapter is that in the past all specialties showed an over-representation of male doctors. For that reason, we postulate that the drift in the gender composition of past male-dominated specialties towards becoming female-dominated specialties might be mostly due to a shift in doctors' preferences and not due to male doctors suffering from a lack of same-sex mentors. Notwithstanding, female-dominated specialties are equally worrisome from a policy perspective, since the current gender imbalances will deprive future generations of male doctors of same-sex mentors and perpetuate the current occupational segregation.

Our role model identification strategy, similar to the one used in Canes and Rosen (1995), is defined by Neumark and Gardecki (1996) as a *black box* since the role model effect is something that might or might not occur when female doctors are better represented among surgical specialties. Nonetheless, we find that the increased presence of female role models in male-dominated specialties seems to make these more attractive to both male and female doctors. With the data available it is very difficult to disentangle what proportion of the effect is due to informational role models or other exogenous or correlated effects. From a policy maker perspective, it is worth performing a careful examination of which attributes associated with the training hospitals with a higher proportion of female doctors are different from the attributes from other training hospitals. Increasing the representativeness of female doctors seems to make male-dominated surgical specialties more attractive, would reduce the gender pay gap and help in the creation of lobbies aim at achieving a better work-family balance. Further research can follow Neumark and Gardecki (1996) suggestion of looking inside the *black box* and disentangling what specific forms of mentoring might be the most productive.

4.4 Question 2: Does the Spanish specialty allocation system favour male doctors?

The second part of this paper focuses on the analysis of the potential role of the specialty allocation system in the observed occupational segregation. For this purpose, we analyse the effect of a change in the ranking system that is used to allocate doctors to specialty training positions in Spain and test whether it has affected men and women differently.

In August 2010, the Spanish Ministry of Health published a list of modifications to the specialty allocation process in the Official State Gazette (Boletin Oficial del Estado 2010). The main change was the increase of the importance of the results in the MIR State Exam to the detriment of the weight given to the grade point average (GPA). Specifically, the weight given to the MIR score increased from 75% to 90% and as a result the contribution of the GPA decreased from 25% to 10%. The justification, provided in the official document, was to ensure the objectivity of the process in the face of an increasing number of non-Spanish medical graduates taking part in it. The results from the MIR examination were viewed as more objective than the GPA, as all candidates take the same test at the same date. The GPA is considered to be more prone to biases associated with idiosyncrasies from the university (or country) issuing the postgraduate medical certificate. Therefore, the institutional aim of the new ranking system is the enhancement of the prospects of Spanish-graduate doctors. Nonetheless, we conjecture that the change might have had some unintended consequences in terms of gender balance, as male and female doctors might have reacted differently to the increased importance of the MIR examination.

According to Dávila-Quintana et al. (2015) the outcomes of the MIR exam are the result of a relatively short but very intense period of preparation, defined by the authors as *Sprint Effort*, whilst doctor GPAs are the result of a *Long Term Effort*. Those definitions reflect the different nature of the two measures of student performance: the MIR examination being a one shot test in a highly competitive setting, whilst the GPA is the average of a student's performance during undergraduate studies and therefore gives more weight to long term effort and perseverance. Previous literature suggests that female doctors might be worse off with the new ranking system as it has increased the importance of the highly competitive MIR examination. In an economic experiment, Gneezy et al. (2003) found that females may be less effective than men in competitive environments, even if they are able to perform similarly in non-competitive ones. The authors observe that increasing the level of competition improves the performance of men whilst more risk averse women do not react in same way to the introduction of uncertain payments in the tournament analysed. Similarly, Niederle and Vesterlund (2007) and Niederle and Vesterlund (2010) found in another experiment that women are uncomfortable performing in highly competitive settings and as a result choose not to compete and thereby exert less effort than men.

Empirical studies corroborate most of the findings from experimental evidence. Ors et al. (2013) analysed the performance of men and women in a highly competitive entry exam to a French business school and found that the distribution of exam scores for men had higher means and fatter tails than the distribution for women. However, when analysing long-term measures of performance, defined by the authors as *less stressful environments*, women presented better results. Jurajda and Munich (2008) found similar results analysing admission to university in the Czech Republic. The authors compared the admission outcomes of equally able men and women, finding that both groups perform similarly well when competition to admission is less intense. However, women perform substantially worse when analysing the entry outcomes of highly selective universities. If the female doctors' reaction to the increase in the competitiveness of the MIR process is similar to the observed behaviour of women in this literature, then their ranking outcomes will be lower than the hypothetical ones achieved if the change had not happened.

Worse ranking outcomes for female doctors connect with observed occupational segregation, since most of the male-dominated surgical specialties are in high demand and thus can only be selected by the highest ranking applicants. The combination of high attractiveness and a small supply of training posts leads to a situation where only top ranked students have male-dominated surgical specialties in their choice set. The case of plastic surgery is an extreme example as often this specialty is only available in the choice set of the very top ranked doctors in a given year[36] leaving students who

[36]In the specialty allocation process in 2015 the last training position was given to a student with the rank number 1,047 out of 6,348 and in 2014 the last student held position number 886 out of 6,015.

rank below that threshold with no options. Moreover, taking into account that doctors not only choose their specialty but also location, even marginal changes in the ranking position may put doctors at risk of losing their desired training post. In general, the new weights penalise individuals with a good GPA and reward good performers on the MIR examination.

We test the differences in the ranking position achieved by doctors that result from the introduction of the new weights by means of a test of equality of means and a non-parametric approach, the Wilcoxon Rank-Sum test. We find statistically significant differences between male and female doctors, as the latter are on average worse off than men after the change. The differences are more pronounced in the top half of the ranking distribution, meaning that female doctors on average have reduced their probability of accessing the most demanded specialties. Our results confirm that the policy change, whose primarily aim was to reduce biases and to favour Spanish qualified doctors, have had, at least for the studied cohorts, an unintended consequence of reducing the ranking position achieved by female doctors and hence have lowered their probabilities of accessing the most desired specialties.

4.4.1 Data

We use the information on doctors included in the MIR Registry, database described in detail in section 4.3.1. We analyse the outcomes of the specialty allocation process for the years 2013 and 2015, where 6,348 and 6,015 doctors chose a specialty training post, respectively. From the MIR Registry we use the variables *GPA*, the grade point average, and the variable *ES*, that refers to MIR examination score, to compute doctors' pre and post-change ranking positions, given by the variables $RankOld$ and $RankNew$, respectively. Section 4.4.2 describes in detail the construction of the variables $RankOld$, $RankNew$ and $RankDif$. The latter is our main interest and captures, for each doctor, the difference in the ranking position that resulted from the introduction of the new weights. The variable *ES* is only available for years 2013 and 2015; both years are from the period post-change in weights, and therefore we are not able to test how the change would have modified the ranking of the doctors who

Similar results are found for previous years.

chose a specialty before the change was implemented.

The MIR Registry includes a variable that indicates doctors' original ranking position, *Original Rank*. Figure 4.3 shows the distribution of *Original Rank* for the years 2013 and 2015. We observe how beyond the *Original Rank* position 3,500 the number of doctors who opt out of the process increases dramatically.[37] Although, the total number of training positions available was equal to 6,348 in 2013 and 6,015 in 2015, doctors who originally ranked below those thresholds could opt to one of the remaining training posts. The last doctor who chose a specialty in 2013 had an *Original Rank* position equal to 9,182 and this position was equal to 8,533 in 2015.

For most doctors the *Original Rank* does not coincide with the actual order in which they made their specialty choices (captured by variable $RankNew$). Notwithstanding, for most doctors the discrepancy between the original and the actual ranking is minimal and the results we obtain comparing $RankOld$ and $RankNew$ should be very similar to those we would obtain using *Original Rank*. However, we cannot use the latter as we do not observe the characteristics of the individuals who drop out of the process, i.e. their *GPA*, *ES* and gender.[38] In order to test differences in the distribution of $RankDif$ across groups we employ two other variables from the MIR Registry: *Women* and *Spanish* that have been previously described in Section 4.3.1.

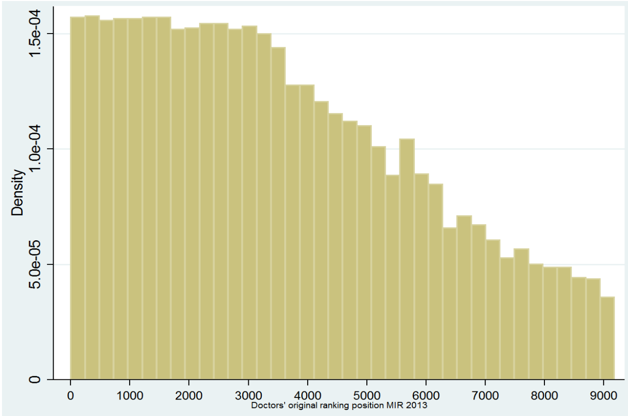
4.4.2 Methodology

The ideal assessment of the effect of the change in the ranking system requires knowledge of how the same individual would behave in the pre and post-weights change periods. We would require a counterfactual observation for each individual indicating what the outcome would have been if the change would have not taken place. However, as described in the previous section, our data comes from doctors who participated in the specialty allocation process after the introduction of the new weights and, therefore, to assess the effect of the change we need to assume that the new weights have neither affected medical students' *GPAs* nor MIR examination

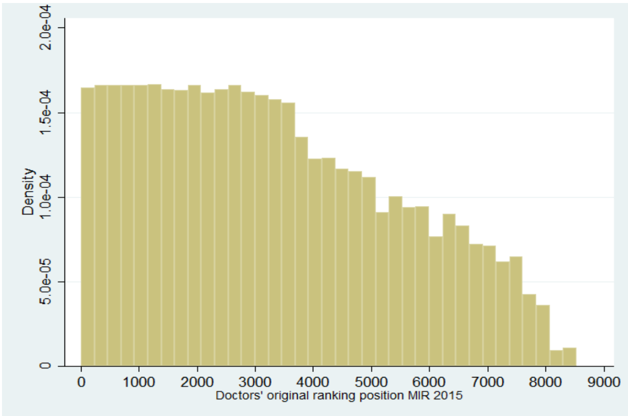
[37] Doctors for whom there is no suitable alternative left at the moment of the choice can opt out of the process that year and opt for a position in future calls.

[38] A direct comparison between the original and actual ranking position shows that in 2013 (2015) the average difference between the two measures for the first 3,500 top ranked doctors was 20 (16).For the first 5,000 doctors the difference increases to 100 (101) positions, whilst when comparing the average difference for the complete sample the number goes as high as 858 (297).

Figure 4.3: Distribution of doctors according to their original ranking position



(a) MIR cohort 2013



(b) MIR cohort 2015

scores. This is quite a restrictive assumption, especially for the results of the MIR examination. It is likely that a medical student in the face of the increased importance of the MIR examination would respond to the change by exerting more effort in the exam preparation. It is well-known that students adapt their exam preparation effort to their desired specialty (Arcidiacono and Nicholson 2005) and that the increase in competition could have increased the effort in preparation for all doctors but that the effect might be larger for men than women (Niederle and Vesterlund 2007; Niederle and Vesterlund 2010).

However, the change in weights may not have affected the GPA, or if so only very mildly. The GPA is a long-term measure that combines the effort of the student from the first to the sixth year of medical undergraduate studies. The change in the weights took place in 2010 when most students from the 2013 data cohort were at least in their fourth year of medical studies and those from the 2015 cohort were at least in their second year. It seems unlikely that students would modify their long term strategy half-way through their bachelor's degree. Most students do not decide what specialties they would like to practise until the final stage of their medical studies (Goldacre et al. 2010) and, therefore, GPA may be a fair representation of their best effort in order to keep all options open. All things considered, by failing to include a counterfactual observation in the analysis we could be underestimating or overestimating the effect of the change in the weights, therefore underestimating or overestimating the magnitude of the rank differences between men and women. We expect that the change has modified both female and male doctors' strategies in the current circumstances however, as literature suggests, it might have increased competition and effort disproportionately between men and women.

The variable $RankDif$ quantifies the difference in the actual ranking position caused by the change in weights. It results from the subtraction of the ranking position achieved with the new weights, represented by the $RankNew$, from the position that the individual would have achieved with the pre-change weights represented by variable $RankOld$ and this relationship is shown by expression (4.7) where $I = \{i \in \mathbb{N} : 1 \leq i \leq \bar{I}\}$ represents the set of doctors.

$$\begin{aligned} RankDif_i &= RankOld_i - RankNew_i \\ RankDif_i &= F(TotalScore_{old,i}) - F(TotalScore_{new,i}) \end{aligned} \tag{4.7}$$

Both $RankOld$ and $RankNew$ result from applying the ranking function to the weighted combination of ES and GPA, as reflected in expression (4.8). ES and GPA are weighted by fixed values represented by α and β, as reflected in expression (4.9); α corresponds to the average scores of the top ten MIR examinations, $\{ES_{i(k)} : i(k) \in I, : 1 \leq k \leq 10\}$, whilst β to the average of the top ten GPAs of the cohort, $\{GPA_{i(k)} : i(k) \in I, : 1 \leq k \leq 10\}$. For each doctor, represented by i, we compute the variable $RankDif$, that equals zero if the doctor keeps the same ranking order with the two different set of weights, i.e. $RankNew_i = RankOld_i$. It is smaller than zero if the doctor is worse off with the new weights, i.e. $RankNew_i < RankOld_i$, and greater than zero if the doctor is better off, i.e. $RankNew_i > RankOld_i$.

$$
\begin{aligned}
TotalScore_{old,i} &= \frac{75}{\alpha}ES_i + \frac{25}{\beta}GPA_i \\
TotalScore_{new,i} &= \frac{90}{\alpha}ES_i + \frac{10}{\beta}GPA_i
\end{aligned}
\tag{4.8}
$$

$$
\text{where} \quad \alpha = \frac{\sum_{k=1}^{10} ES_{i(k)}}{10} \quad \text{and} \quad \beta = \frac{\sum_{k=1}^{10} GPA_{i(k)}}{10} \tag{4.9}
$$

To test if the change in weights affect men and women differently, we perform a test of equality of means to the variable $RankDif$. We assume a common variance for the individuals of the same gender but allow the variance to be different between men (m) and women (w). The test for equality of means is given by expression (4.10), where μ represents the mean and s the standard deviation of the variable $RankDif$, N_m and N_w the number of male and female doctors, and t follows a Student's t distribution.

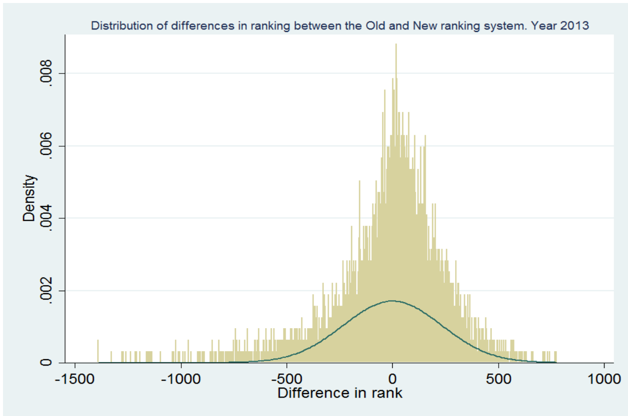
$$
t = \frac{\mu_m - \mu_w}{\sqrt{\dfrac{s_m^2}{N_m} + \dfrac{s_w^2}{N_w}}} \tag{4.10}
$$

Moreover, as $RankDif$ only takes integers and its distribution might cast doubt on its normality (see Figure 4.4), we also apply a non-parametric approach, the Wilcoxon Rank-Sum Test (Wilcoxon 1945; Mann and Whitney 1947) that tests null the hypothesis that two samples (i.e. $RankDif$ for male and female doctors) are from populations with the same distribution. The construction of Wilcoxon statistic T involves jointly ranking the values of $RankDif_i$ from smallest to largest of both men and women, whose sample sizes are given by n_m and n_w, respectively. The smallest $RankDif_i$ is given the value 1 whilst the largest is given the value $n = n_m + n_w$. The second step is to sum the ranking numbers associated with the observations of the group that we denote as first, in this case the one comprised of male doctors, as given by (4.11).

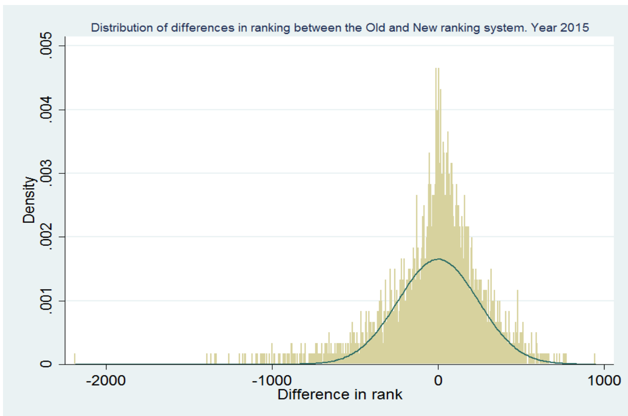
$$
T = \sum_{i=1}^{n_m} R_{1i} \tag{4.11}
$$

As the sample size is sufficiently large, we can use the normal approximation given

Figure 4.4: Distribution of the differences in ranking represented by the variable $RankDif$



(a) MIR cohort 2013



(b) MIR cohort 2015

by expression (4.12)

$$z = \frac{T - E[T]}{\sqrt{Var(T)}} \tag{4.12}$$

where $E[T] = \frac{n_m(n+1)}{2}$, $Var[T] = \frac{n_m n_w}{n} s^2$ and s is the standard deviation of the combined ranking. Finally, we compute the probability of observing that $RankDif_{Men} > RankDif_{Women}$ for any two random observations, and this is given by expression (4.13).

$$Pr(RankDif_{Men} > RankDif_{Women}) = \frac{2T - n_m(n_m+1)}{2n_m n_w} \tag{4.13}$$

We sort individuals according to their actual ranking position ($RankNew$) and divide them into 13 groups. The top group encompasses the top 499 achievers and the bottom group the doctors who chose a specialty training post in the position 6,000 or below. We present the differences in means between men and women for the variable $RankDif$, represented by $\Delta RankDif$ where $\Delta RankDif = \overline{RankDif}_{men} - \overline{RankDif}_{women}$, and its statistical significance is given by the results of the t-test and Wilcoxon test for the aggregated total and for each of the 13 groups. The objective is to analyse if the change in weights affects top, middle and bottom ranked students differently. We also present the results of the $RankDif$ for the reduced sample of students who graduated from a Spanish university to check whether the gender gap in $RankDif$ is also present in the more homogeneous group of Spanish graduates and to test whether the policy fulfils its original purpose.

4.4.3 Results

4.4.3.1 Results MIR 2013

Table 4.10 shows the descriptive statistics for the variable $RankDif$ by gender, reports the differences in means represented by $\Delta RankDif$, the results of the t-test and the Wilcoxon Rank-Sum test for the population of doctors who chose their specialty in the year 2013. There were 6,348 doctors and from those 2,106 were men and 4,242 women. On average, male doctors gain 11.4 positions whilst female doctors lose 5.7

positions. Therefore, $\Delta RankDif$ indicates a difference of 17.1 positions between the two groups and this is statistically significant at the 95% confidence level. The results from the Wilcoxon test are also statistically significant and show that the probability of observing $RankDif_{Men} > RankDif_{Women}$ is 0.53, suggesting that the distribution of the variable $RankDif$ is different for men and women.

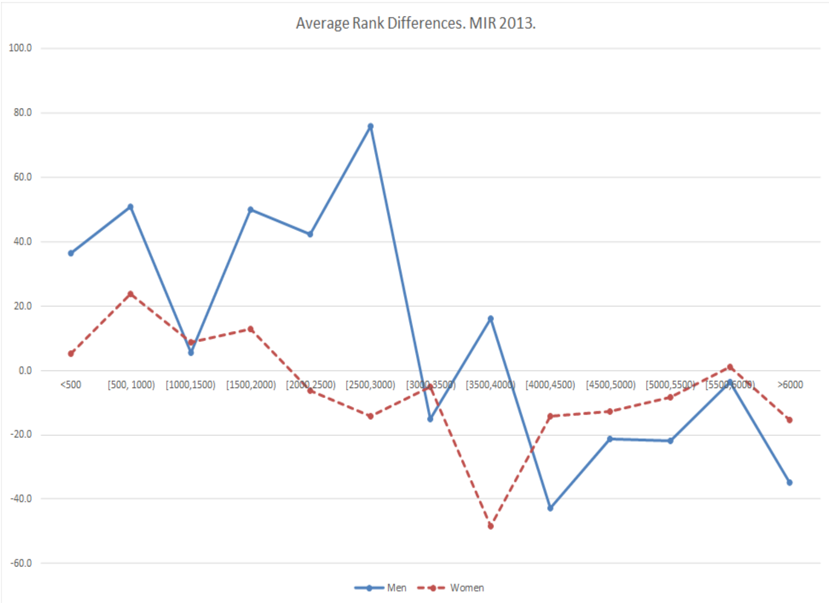
We also show the descriptive statistics and the differences in means for male and female doctors grouped according to their ranking position. An equal distribution of them across groups would require an equal share of men and women, with respect to the total number of men and women, in each group. However, the distribution we observe is far from being equal and the largest difference can be found in the group of top achievers (< 500), where the share of male doctors is 10% whilst the share of female doctors is only 6.8%. In addition, $\Delta RankDif$ for the group of top achievers is positive, equalling 31.3 and being statistically significant at the 99% confidence level. The breakdown of $RankDif$ for that group suggests that both male (36.5) and female (5.2) doctors gain positions with the introduction of new weights, but that the improvement is bigger for male doctors.

In general we observe a clear gender gap in the distribution of the $RankDif$, as Figure 4.5 shows. All the statistically significant $\Delta RankDif$ are positive, and for all groups at the top end of the ranking, i.e. those doctors who ranked in the first 3,000 positions, differences are always positive, meaning that a typical top achieving male doctor gains, on average, more positions than the equivalent top achieving female doctor. The results of the non-parametric Wilcoxon Rank-Sum test are similar to the results observed for the test of equality of means.

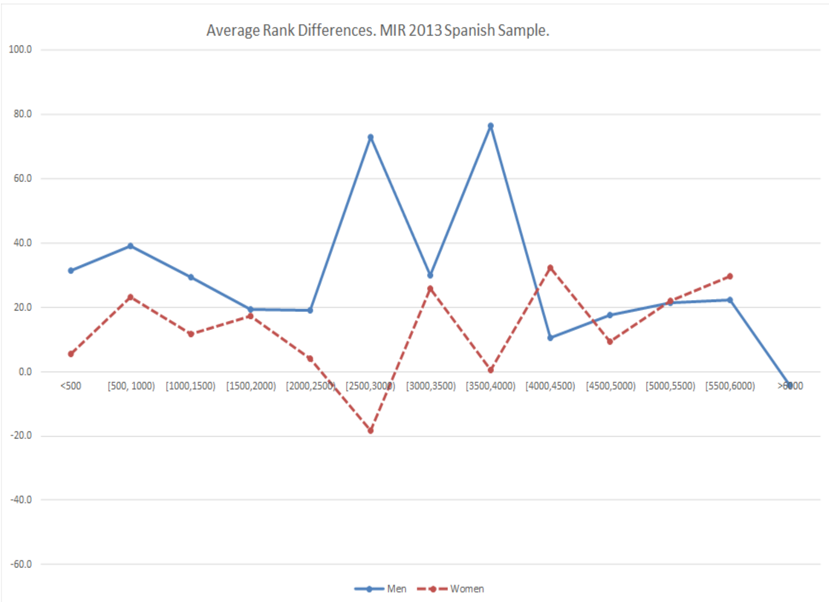
4.4.3.2 Results MIR 2013. Spanish sample

Table 4.11 shows the descriptive statistics, the t-test and Wilcoxon Rank-Sum test for the sample of doctors who graduated from a Spanish university and chose a specialty in the year 2013. The sample size is 4,762, among which 1,335 are men and 3,427 are women. In this sample, as in Table 4.10, we observe that male doctors are over-represented in the two top groups of high achievers (< 500) and $[500, 1000)$. The $\Delta RankDif$ for the entire sample is positive, equalling 17.8 and being statistically significant at the 99% confidence level. In the Spanish sample, both male and female

Figure 4.5: Average $RankDif$ by gender. MIR 2013



(a) All Doctors



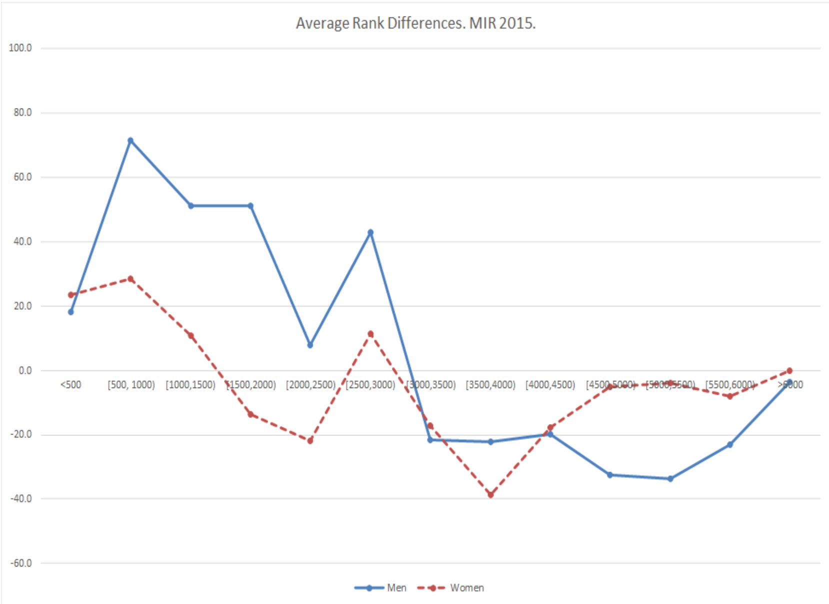
(b) Spanish Sample

doctors are better off with the introduction of the new weights, however the magnitude of the gain is greater for men, who gain on average 31 positions, than for women, who *only* gain 13.2. The Wilcoxon test confirms the previous result and shows that the probability of observing $RankDif_{Men} > RankDif_{Women}$ is 0.53 and statistically significant at the 99% confidence level. That result suggests that the distribution of the variable $RankDif$ is also different between men and women for the restricted sample who graduated in Spain. In general, the results are very similar to the ones in Table 4.10, however the magnitude of the variable $\Delta RankDif$ is smaller for the top achievers and larger for doctors situated in the central positions of the ranking distribution as Figure 4.5 shows.

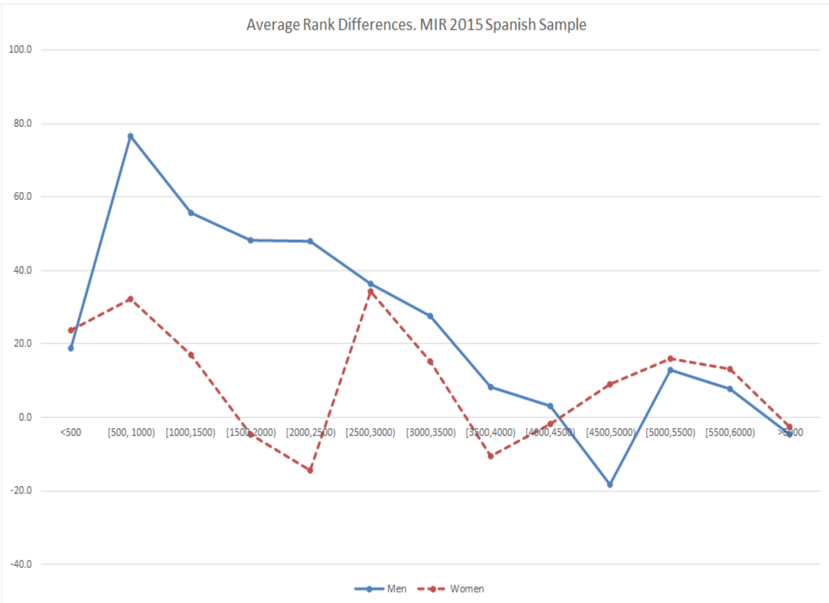
4.4.3.3 Results MIR 2015

Table 4.12 shows the descriptive statistics, the results from the t-test and the Wilcoxon Rank-Sum test for the sample of doctors who took part in the MIR in 2015. In this case, the total number of doctors equals 6,015, of which 2,064 are male and 3,951 female. On average, male doctors gained 10.4 positions whilst female doctors lost 5.4 positions. Therefore, this indicates a difference of 15.7 positions between the two groups that is statistically significant at the 95% confidence level. The results from the Wilcoxon test are also statistically significant at the 99% confidence level and show that the probability of observing $RankDif_M > RankDif_W$ is 0.52, indicating that the distribution of the variable $RankDif$ is different for men and women. In 2015, $\Delta RankDif$ for the group of top achievers is negative, meaning that the women from the top group gained, on average, more positions than men with the introduction of the new weights. However, the negative difference fails to be statistically significant. $\Delta RankDif$ is statistically significant for the groups $[500, 1000)$ and $[1500, 2000)$ and equal to 43.2 and 64.8, respectively. There is another statistically significant $\Delta RankDif$ at the 90% confidence level for the group $[5000, 5500)$, it is negative and equal to -29.9, indicating that women at the bottom of the ranking distribution are better off than men, after the change in weights. Figure 4.6 shows the distribution of $RankDif$ for the MIR 2015.

Figure 4.6: Average $RankDif$ by gender. MIR 2015.



(a) All Doctors



(b) Spanish Sample

4.4.3.4 Results MIR 2015. Spanish sample

Table 4.13 does likewise for the reduced sample that only included those doctors who graduated from a Spanish university. The overall $\Delta RankDif$ is again positive, equal to 19.2, and it is statistically significant at the 99% confidence level. In this case, both male and female doctors are better off with the introduction of the new weights, however the magnitude of the gain is greater for men who gain on average 29.5 positions, whilst women gain 10.3. The discrepancy between the distribution of $RankDif$ for male and female doctors is confirmed by the Wilcoxon test, as the probability of observing $RankDif_{Men} > RankDif_{Women}$ is 0.53 and statistically significant at the 99% confidence level. The breakdown of $\Delta RankDif$ by ranking group present similar results to those observed in Table 4.12 for the complete sample.

4.4.4 Discussion

Our results show that the policy change that increased the weight of the MIR examination, to the detriment of the weight associated with the grade point average, has overall favoured male doctors. On average, female doctors lose ranking positions, with respect to the position they would have achieved with the old weights, whilst male doctors gain positions. The differences are statistically significant. The results for the reduced sample of Spanish graduates specifically show that, on average, both male and female doctors are better off after the change, however the magnitude of the gain is substantially smaller for the female doctors. Similarly, the breakdown of the ranking differences by ranking position shows that top achievers, both men and women, are better off than bottom achievers after the change; however, the magnitude of the gain is again smaller for female top achievers than for male top achievers.

The results from the bottom half of the ranking distribution need to be interpreted with caution, as the number of doctors opting out of the MIR process increases dramatically when the number of training positions reduces. Hence, the discrepancies between the original ranking and the actual choice order are larger here than among the top achievers. We expect the proportion of male doctors dropping out of the process to be larger than the proportion of females, as historically male doctors have shown stronger preference for the most demanded specialties and, therefore, bottom achieving female doctors who historically have shown preference for the less demanded specialties such as general practice, might be over-represented at the bottom of the ranking distribution. If the latter is confirmed and we only observe fewer and/or worse-achiever males, it would (partially) explain the observed change in trends at the bottom half of the ranking distribution.

Our results corroborate the well-known gender gap in competitiveness (Frick 2011). Croson and Gneezy (2009) summarize the findings from experimental economics concluding that women are more reluctant to engage in competitive interactions and as the competitiveness of an environment increases, the performance and participation of men increase relative to women. Frick (2011) suggests that the reluctance is usually explained by women's higher levels of risk aversion and also with an excess entry in the competition level of men due to their overconfidence. These differences in risk and confidence are consistent with the observed strategies taken by female and male doctors on the MIR examination. Romeo-Ladrero (2014) constructed a measure of risk taken in the MIR examination[39] finding that males take greater risk than female doctors, and that translates to better results for the top achievers and worse results for the male doctors at the bottom end of the ranking distribution. The observed behaviour by Romeo-Ladrero (2014) is very similar to our results for the distribution of $\Delta RankDif$. The differences in ranking are, on average, positive, favouring male doctors in the top half of the ranking distribution; specifically, male top achievers who might have taken more *risk* and where their behaviour entails an increase in their MIR score. By contrast, male doctors in the bottom half of the ranking distribution might also have taken more *risk* in responding to the test, however that group presents a lower success rate, as they are more likely to have incorrect answers, and for them the extra risk taken translates to a negative $\Delta RankDif$.

The original design of the MIR allocation system and the posterior change in weights were motivated to ensure the reliability and transparency of the process, and to avoid favouritism (Aranda 2016). The Spanish specialty allocation system is based on the principle of vertical equity, as it permits the most productive candidates to have the

[39] The author defines it as the ratio of the total answered questions by the total number of questions in the multiple choice test. The test rewards correct answers with three points and penalizes incorrect answers with the subtraction of one point.

highest priority in choosing a training programme, using ranking position as a proxy for doctors' productivity (Harris et al. 2014). Nonetheless, our findings suggest that ranking position might not be a fair proxy of productivity, as there is a clear differential in attainment on the MIR examination results between male and female doctors. The MIR examination only evaluates medical knowledge, by means of a restrictive multiple choice test, does not value other important aspects such as communication, empathy or professionalism (Aranda 2016), and neglects the importance of having real vocation for the chosen specialty (Lorusso and González López-Valcárcel 2013). For those other non-valued aspects there is evidence of females outperforming male doctors. Using data from the United Kingdom, Dewhurst et al. (2007) and Woolf et al. (2011) found that women were more likely to outperform men in clinical skill examinations that take place during the specialty training residency. Moreover, Baumhäkel et al. (2009) found that females are more likely to adhere to clinical guidelines and Lurie et al. (1993) shows that female doctors provide preventive care more often than male doctors.

Dávila-Quintana et al. (2015) describe the two criteria the MIR allocation process should meet: vertical equity and social efficiency. Although the design of the system was made to ensure the first criteria, the results of our analysis suggest that the equity criteria is being violated. The social efficiency described as the capacity of the cohort of specialist doctors to maximise the number QALYs[40] of a given population is also neglected (Dávila-Quintana et al. 2015). Therefore, there is a need for an in depth revision of the functioning of the process in order to adapt it to the socio-demographic composition of new cohorts of doctors, to the actual role of doctors in society, and to make it accountable for the other competences that are valued in the practise of medicine in the XXI century (Torres et al. 2008; Lorusso and González López-Valcárcel 2013).

4.5 Conclusion

This paper extensively explores two of the sources of the occupational gender segregation in the Spanish medical workforce. First, we analysed whether the presence of

[40]Quality-Adjusted Life Year

female role models in male-dominated specialties affects the career choices of female doctors. Our results suggest that an increased presence of females in those specialties is an attractor for both male and female doctors. For the reduced sample of female doctors with an interest in surgical specialties, the effect is stronger, as being exposed to a larger proportion of female role models makes them more likely to choose a male-dominated surgical specialty, with respect to a gender-balanced surgical option. Notwithstanding, the estimation of social effects is challenging and we cannot discard the presence of other elements correlated with a larger proportion of female role models that might also influence doctors' specialty choices.

Second, we analysed the functioning of the specialty allocation system and tested whether a policy change, aimed at increasing the vertical equity of the process, had the unintended consequence of reducing the probability of female doctors accessing high demand specialties. We find that the increase of the competitiveness of the process, which results from the greater weight associated with the MIR examination score, has made female doctors, on average, worse off. However, the breakdown of the differences in the ranking position shows that although top achiever female doctors gain positions with the introduction of the new weights, the magnitude of those gains is always smaller than the gains displayed by male doctors. The gender gap in competitiveness is poorly understood (see Frick (2011) for classification of the main theories addressing the issue), however the aim of this paper is not disentangling why the two groups present different levels of competitiveness. Our results are the evidence that those differences also exist in the Spanish medical market and, in consequence, lower the probability for female doctors to access the most demanded specialties.

Overall, our findings confirm that the observed gender gap in surgical specialties is not only due to differences in intrinsic preferences between men and women. Although, in this chapter we only explore two of the possible sources that give rise and help in perpetuating occupational segregation and its undesired consequences, we conjecture that there are many other elements which also contribute, and that require a careful examination. This is an unexplored area where further research is required.

The Spanish specialty allocation process dates from the late nineteen seventies when the medical workforce composition was very different from the actual workforce composition. There is a need for policy makers to better understand the mechanisms that give rise to the allocation of new cohort of doctors to specialties. This exercise gains importance with the feminization of the medical workforce and further understanding of how gender influences doctors' careers choices becomes required. Arrizabalaga et al. (2015) suggest that the recognition of gender inequalities by medical institutions is the first step in helping women to advance in their careers.

Acknowledgements

I am grateful to Beatriz Gonzalez and her research team from Universidad de Las Palmas de Gran Canaria for providing the data and for sharing their knowledge on the Spanish specialty allocation market.

4.6 Tables

Table 4.1: List of specialties in the Spanish Health System

Laboratory	Clinical Analysis, Anatomical Pathology, Clinical Biochemistry, Pharmaceutical Medicine, Immunology, Nuclear Medicine, Microbiology, Clinical Neurophysiology, Radiology
Medical	Allergy, Anaesthetists, Cardiology, Gastroenterology, Endocrinology and Diabetes, Geriatric, Haematology, Medical Hydrology, Occupational Medicine, Sport and Exercise Medicine, General Practice, Rehabilitation Medicine, Intensive Care Medicine, General Internal Medicine, Legal and Forensic Medicine, Public Health, Renal Medicine, Respiratory, Haematology, Neurology, Medical Oncology, Clinical Oncology, Paediatrics & Rheumatology.
Surgical	Cardiovascular Surgery, General Surgery, Oral Surgery, Paediatric Surgery, Plastic Surgery & Thoracic Surgery, Neurosurgery
Medical-Surgical	Vascular Surgery, Dermatologic Surgery, Obstetrics & Gynaecology, Ophthalmology, Otorhinolaryngology, Genito-Urinary Medicine & Orthopaedic Surgery.

Table 4.2: Classification of surgical and medical-surgical into male-dominated and gender-balanced specialties

Male dominated *surgical* and *medical-surgical* specialities	Vascular Surgery, Cardiovascular Surgery, Oral Surgery, Orthopaedic Surgery, Plastic Surgery, Thoracic Surgery, Neurosurgery and Urology
Gender balanced *surgical* and *medical-surgical* specializations	General Surgery, Dermatology, Obstetrics & Gynaecology, Ophthalmology, and Otorhinolaryngology

The classification of specialties into male-dominated or gender balanced respond to historical ratios. The specializations for which the intake of female residents has been less than 50% for most years in the period 1991- 2014 are classified as male-dominated.

Table 4.3: Variables in the MIR Registry and MIR Survey datasets

MIR Registry	
Specialty Chosen	Categorical variable indicating individual's chosen specialty (47 specialties)
Ranking Position	This variable indicates the order in which the individual made the specialty choice
Training Location	Categorical variable indicating the university hospital where the individual carries out the specialty training
Women	Equals 1 if the individual is female and 0 otherwise
Age	The variable indicates individual's age during the specialty allocation process
Spanish	Equals 1 if the individual's nationality is Spanish and 0 otherwise
GPA	Grade Point Average (GPA) of medical undergraduate studies, that is continuous and ranges from 1 to 5
Exam Score (ES)	Numerical variable that provides the results of the MIR state examination
Medical School	Categorical variable: 34 Spanish medical schools
Year	The variable indicates the year in which the individual participated in the specialty allocation process
MIR Survey	
Preferred Specialty	Categorical variable indicating individuals' preferred specialty (47 specialties)
First MIR	Equals 1 if the doctor is participating in the MIR allocation process for the first time and 0 otherwise

[a] The MIR Survey also includes all the variables from the MIR Registry.

Table 4.4: Example of role model exposure for a doctor who started medical school in the academic year 2006/07

Academic Year	Did the student attend clinical training at a university hospital?	Who are the role models? All female junior doctors who chose specialization from year:
1^{st}2006/7	No	
2^{nd}2007/8	No	
3^{rd}2008/9	Yes	2003 (5^{st} year residents) to 2008 (1^{th} year residents)
4^{th}2009/10	Yes	2004 (5^{st} year residents) to 2009 (1^{th} year residents)
5^{th}2010/11	Yes	2005 (5^{st} year residents) to 2010 (1^{th} year residents)
6^{th}2011/12	Yes	2006 (5^{st} year residents) to 2011 (1^{th} year residents)

Table 4.5: Description of the dependent variables y_1, y_2 and y_3

Dependent Variables	Values	Sample size
y_1	1 if doctor's *Preferred Speciality* is a male-dominated *surgical* or *medical-surgical* specialty 0 if 1 if doctor's *Preferred Speciality* is any other option (*laboratory*, *medical*, gender-balanced *surgical* and gender-balanced *medical-surgical*)	All respondents to the MIR Survey N= 6,183
y_2	1 if doctor's *Preferred Speciality* is a *surgical* or *medical-surgical* specialty (all male-dominated and gender balanced specializations) 0 if 1 if doctor's *Preferred Speciality* is any other option (*laboratory* or *medical*)	All respondents to the MIR Survey N= 6,183
y_3	1 if doctor's *Preferred Speciality* is a male-dominated surgical or medical-surgical specialty 0 if doctor's *Preferred Speciality* is a gender-balanced *surgical* or *medical-surgical* specialty	Only doctors for whom the variable *Preferred Speciality* is a *surgical* o *medical-surgical* N=2,183

Table 4.6: Descriptive statistics MIR Survey

	All respondents to the MIR Survey					Role Model Sample				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Women	8,739	0.678	0.467	0	1	6,261	0.718	0.450	0	1
Age	8,656	27.04	4.563	22	51	6,209	25.352	2.298	22	51
Spanish	8,347	0.860	0.347	0	1	6,235	0.987	0.112	0	1
Year MIR										
2013	8,739	0.351	0.477	0	1	6,261	0.296	0.457	0	1
2014	8,739	0.259	0.438	0	1	6,261	0.254	0.435	0	1
2015	8,739	0.390	0.488	0	1	6,261	0.450	0.498	0	1
GPA	8,739	1.945	0.484	1	4.3	6,261	1.963	0.468	1	4.2
MIR Exam Score (ES)	8,739	390.53	79.59	174	591	6,261	404.92	74.52	177	591
Ranking Position	8,739	3204.17	2194.13	1	9176	6,261	2839.39	2078.52	1	9108
First MIR	8,692	0.776	0.417	0	1	6,221	0.926	0.262	0	1
Year finish studies	3,408	2012.982	3.099	1980	2014	2,820	2013.70	0.999	2007	2014
RM1	6,261	0.653	0.161	0	1	6,261	0.653	0.161	0	1
Dependent Variables										
y_1	8,738	0.206	0.405	0	1	6,261	0.203	0.402	0	1
y_2	8,739	0.357	0.479	0	1	6,261	0.354	0.478	0	1
y_3	4,091	0.436	0.496	0	1	2,891	0.437	0.496	0	1
Preferred Specialty										
Laboratory	8,739	0.064	0.245	0	1	6,261	0.046	0.208	0	1
Medical	8,739	0.578	0.494	0	1	6,261	0.600	0.490	0	1
Medical-surgical	8,739	0.257	0.437	0	1	6,261	0.257	0.437	0	1
Surgical	8,739	0.100	0.300	0	1	6,261	0.098	0.297	0	1
Chosen Specialty										
Laboratory	8,739	0.075	0.264	0	1	6,260	0.053	0.223	0	1
Medical	8,739	0.720	0.449	0	1	6,260	0.725	0.446	0	1
Medical-surgical	8,739	0.152	0.359	0	1	6,260	0.166	0.372	0	1
Surgical	8,739	0.059	0.235	0	1	6,260	0.065	0.246	0	1
University										
AU Barcelona	8,680	0.049	0.216	0	1	6,261	0.063	0.242	0	1
AU Madrid	8,680	0.036	0.186	0	1	6,261	0.045	0.207	0	1
Alcala	8,680	0.022	0.146	0	1	6,261	0.027	0.161	0	1
Alicante	8,680	0.023	0.149	0	1	6,261	0.029	0.167	0	1
Badajoz	8,680	0.017	0.128	0	1	6,261	0.020	0.139	0	1
CEU	8,680	0.005	0.070	0	1	6,261	0.002	0.042	0	1
Castilla -Mancha	8,680	0.015	0.122	0	1	6,261	0.021	0.142	0	1
Cadiz	8,680	0.023	0.149	0	1	6,261	0.027	0.163	0	1
Cantabria	8,680	0.012	0.109	0	1	6,261	0.015	0.121	0	1
Catolica StVicente	8,680	0.003	0.051	0	1	6,261	0.004	0.061	0	1
Complutense Madrid	8,680	0.065	0.246	0	1	6,261	0.078	0.268	0	1
Cordoba	8,680	0.022	0.146	0	1	6,261	0.026	0.160	0	1
Europea Cees	8,680	0.002	0.043	0	1	6,261	0.003	0.050	0	1
Gerona	8,680	0.003	0.059	0	1	6,261	0.005	0.069	0	1
Granada	8,680	0.045	0.208	0	1	6,261	0.054	0.227	0	1
Int Catalua	8,680	0.003	0.058	0	1	6,261	0.005	0.068	0	1
Laguna	8,680	0.020	0.141	0	1	6,261	0.026	0.158	0	1
Lleida	8,680	0.009	0.097	0	1	6,261	0.007	0.085	0	1
Malaga	8,680	0.028	0.164	0	1	6,261	0.033	0.180	0	1
Murcia	8,680	0.029	0.169	0	1	6,261	0.038	0.192	0	1
Navarra	8,680	0.026	0.160	0	1	6,261	0.033	0.178	0	1
Oviedo	8,680	0.018	0.132	0	1	6,261	0.021	0.143	0	1
Pais Vasco	8,680	0.034	0.182	0	1	6,261	0.044	0.205	0	1
Rey JC	8,680	0.004	0.066	0	1	6,261	0.006	0.078	0	1
Salamanca	8,680	0.022	0.148	0	1	6,261	0.028	0.164	0	1
Santiago	8,680	0.041	0.198	0	1	6,261	0.051	0.221	0	1
Sevilla	8,680	0.049	0.215	0	1	6,261	0.058	0.234	0	1
Tarragona	8,680	0.016	0.125	0	1	6,261	0.020	0.140	0	1
UB BCN	8,680	0.044	0.206	0	1	6,261	0.058	0.235	0	1
ULPGC	8,680	0.012	0.107	0	1	6,261	0.015	0.120	0	1
Valencia	8,680	0.046	0.209	0	1	6,261	0.056	0.230	0	1
Valladolid	8,680	0.027	0.163	0	1	6,261	0.034	0.181	0	1
Zaragoza	8,680	0.041	0.197	0	1	6,261	0.050	0.218	0	1
European	8,680	0.088	0.284	0	1					
Latin America	8,680	0.090	0.286	0	1					
Other International	8,680	0.010	0.101	0	1					

Table 4.7: Estimation results variable y_1

	(1) All Sample		(2) All Sample		(3) Only Men		(4) Only Women	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Women	-0.460***	-0.093***	-0.459***	-0.093***				
	(0.048)		(0.049)					
Age	-0.026***	-0.005***	-0.026***	-0.005***	-0.029***	-0.008***	-0.022**	-0.004**
	(0.007)		(0.007)		(0.006)		(0.011)	
Spanish	-0.109	-0.022	-0.107	-0.022	-0.175	-0.048	-0.080	-0.014
	(0.203)		(0.203)		(0.243)		(0.218)	
Role Model (RM1)			1.062***	0.214***	1.354***	0.370***	0.933***	0.162***
			(0.214)		(0.359)		(0.221)	
GPA	-0.008	-0.002	-0.008	-0.002	0.033	0.009	-0.029	-0.005
	(0.070)		(0.070)		(0.041)		(0.091)	
First Mir	-0.267***	-0.054***	-0.273***	-0.055***	-0.488***	-0.133***	-0.137***	-0.024***
	(0.067)		(0.064)		(0.089)		(0.049)	
AUMadrid	0.166	0.035	0.124	0.024	-0.045	-0.014	0.256	0.036
	(0.171)		(0.164)		(0.131)		(0.215)	
Alcala	-0.184	-0.032	-0.245	-0.038	-0.552*	-0.139*	-0.015	-0.002
	(0.230)		(0.218)		(0.327)		(0.209)	
Alicante	-0.009	-0.002	0.082	0.016	0.030	0.009	0.147	0.019
	(0.150)		(0.160)		(0.057)		(0.220)	
Badajoz	0.314***	0.072***	0.586***	0.144***	0.235*	0.078*	0.848***	0.174***
	(0.119)		(0.153)		(0.139)		(0.253)	
CEU	0.347***	0.080***	0.301***	0.065***	0.142*	0.046*	0.435***	0.069***
	(0.093)		(0.091)		(0.073)		(0.115)	
CMancha	0.029	0.006	0.703***	0.182***	0.387	0.133	0.946**	0.204**
	(0.184)		(0.264)		(0.391)		(0.382)	
Cadiz	-0.110	-0.020	0.006	0.001	-0.253***	-0.072***	0.216	0.029
	(0.102)		(0.115)		(0.027)		(0.146)	
Cantabria	0.239*	0.052*	0.358***	0.079***	0.243	0.081	0.429	0.067
	(0.124)		(0.122)		(0.200)		(0.403)	
CatolicaStVic	0.518***	0.130***	0.438***	0.101***	0.270	0.091	0.266	0.037
	(0.072)		(0.075)		(0.245)		(0.742)	
Complu Mad	0.127***	0.026***	0.010	0.002	-0.276*	-0.078*	0.221**	0.030**
	(0.048)		(0.037)		(0.145)		(0.103)	
Cordoba	-0.152	-0.027	-0.108	-0.018	-0.637***	-0.154***	0.247**	0.034**
	(0.149)		(0.146)		(0.209)		(0.126)	
EuropeaCees	-0.461***	-0.067***	-0.419***	-0.059***	-0.477***	-0.124***	0.000	0.000
	(0.099)		(0.104)		(0.057)		(.)	
Gerona	0.101	0.021	0.214*	0.044*	0.182***	0.060***	0.290*	0.041*
	(0.111)		(0.127)		(0.043)		(0.160)	
Granada	-0.005	-0.001	0.030	0.005	-0.537**	-0.136**	0.363	0.055
	(0.126)		(0.117)		(0.220)		(0.231)	
Int Cat	0.046	0.009	0.053	0.010	0.219***	0.073***	0.000	0.000
	(0.094)		(0.094)		(0.063)		(.)	
Laguna	0.150	0.031	0.236**	0.049**	-0.302	-0.084	0.562**	0.097**
	(0.104)		(0.100)		(0.498)		(0.263)	
Lleida	-0.890***	-0.098***	-0.140	-0.023	0.150	0.049	0.000	0.000
	(0.099)		(0.231)		(0.212)		(.)	
Malaga	0.051	0.010	0.150	0.030	-0.171	-0.050	0.368***	0.055***
	(0.182)		(0.186)		(0.398)		(0.112)	
Murcia	-0.028	-0.005	0.358**	0.079**	0.112	0.036	0.565***	0.098***
	(0.094)		(0.167)		(0.124)		(0.126)	
Navarra	0.118	0.024	0.177	0.036	-0.046	-0.014	0.335	0.049
	(0.124)		(0.126)		(0.176)		(0.234)	
Oviedo	-0.257	-0.042	-0.204	-0.033	-0.454**	-0.119**	-0.013	-0.002
	(0.244)		(0.224)		(0.189)		(0.278)	
Pais Vasco	0.018	0.003	-0.082	-0.014	-0.480***	-0.124***	0.165	0.021
	(0.163)		(0.172)		(0.177)		(0.174)	
Rey JC	-0.412***	-0.062***	-0.299**	-0.045**	-0.437***	-0.115***	-0.172	-0.017
	(0.112)		(0.128)		(0.045)		(0.167)	
Salamanca	0.016	0.003	0.257***	0.054***	-0.159	-0.047	0.562**	0.097**
	(0.105)		(0.086)		(0.208)		(0.223)	
Santiago	0.039	0.008	0.255	0.053	0.015	0.005	0.442*	0.070*
	(0.144)		(0.179)		(0.156)		(0.262)	
Sevilla	0.096	0.020	0.024	0.004	-0.246	-0.070	0.221*	0.030*
	(0.114)		(0.110)		(0.284)		(0.114)	
Tarragona	0.215	0.047	-0.077	-0.013	-0.347	-0.095	0.124	0.016
	(0.248)		(0.208)		(0.216)		(0.246)	
UB BCN	-0.028	-0.005	-0.049	-0.009	-0.114	-0.034	0.046	0.005
	(0.060)		(0.053)		(0.174)		(0.034)	
ULPGC	-0.044	-0.008	0.001	0.000	-0.818**	-0.181**	0.448*	0.072*
	(0.276)		(0.277)		(0.318)		(0.260)	
Valencia	0.240***	0.053***	0.195**	0.040**	-0.265*	-0.075*	0.463***	0.075***
	(0.074)		(0.093)		(0.142)		(0.164)	
Valladolid	0.140	0.029	0.153	0.030	-0.224	-0.064	0.392	0.060
	(0.131)		(0.154)		(0.139)		(0.273)	
Zaragoza	-0.040	-0.007	0.116	0.023	-0.056	-0.017	0.268	0.038
	(0.126)		(0.138)		(0.249)		(0.201)	
Constant	0.158		-0.605		-0.264		-1.379***	
	(0.299)		(0.417)		(0.339)		(0.464)	
N	6,181		6,181		1,745		4,438	
R2	0.036		0.036		0.032		0.014	
Log-Likelihood	-2279.517		-2278.530		-850.775		-1404.595	
AIC	4563.034		4561.060		1705.551		2813.190	

[a] Base outcomes: Gender: Men, Nationality:Non-Spanish, Medical School: Univesidad Autonoma de Barcelona

[b] SE: Standard Errors clustered by MIR year; AME: Average Marginal Effect

[c] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 4.8: Estimation results variable y_2

	(1) All Sample		(2) All Sample		(3) Only Men		(4) Only Women	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Women	-0.102**	-0.038**	-0.101**	-0.037**				
	(0.047)		(0.047)					
Age	-0.031***	-0.011***	-0.030***	-0.011***	-0.027***	-0.010***	-0.032***	-0.012***
	(0.005)		(0.006)		(0.008)		(0.005)	
Spanish	-0.238**	-0.088**	-0.237**	-0.087**	-0.155	-0.058	-0.297***	-0.108***
	(0.096)		(0.094)		(0.208)		(0.086)	
GPA	0.072*	0.026*	0.072*	0.026*	0.113***	0.042***	0.051	0.018
	(0.040)		(0.040)		(0.036)		(0.048)	
First Mir	-0.332***	-0.122***	-0.337***	-0.124***	-0.398***	-0.148**	-0.318***	-0.116***
	(0.061)		(0.060)		(0.194)		(0.028)	
Role Model (RM1)			0.670	0.247	1.393*	0.517*	0.392	0.143
			(0.568)		(0.832)		(0.526)	
AUMadrid	-0.036	-0.014	-0.062	-0.023	-0.078	-0.029	-0.066	-0.024
	(0.178)		(0.154)		(0.166)		(0.139)	
Alcala	-0.176	-0.065	-0.214	-0.077	-0.377	-0.136	-0.152	-0.054
	(0.234)		(0.201)		(0.433)		(0.144)	
Alicante	-0.000	-0.000	0.057	0.022	-0.096	-0.036	0.112	0.042
	(0.291)		(0.328)		(0.104)		(0.400)	
Badajoz	-0.087	-0.033	0.085	0.032	0.331	0.128	-0.044	-0.016
	(0.157)		(0.280)		(0.363)		(0.286)	
CEU	-0.203*	-0.074*	-0.232**	-0.083**	-0.348**	-0.126**	-0.186***	-0.065***
	(0.114)		(0.091)		(0.146)		(0.069)	
CMancha	-0.184*	-0.068*	0.241	0.093	0.604	0.229	0.109	0.041
	(0.102)		(0.450)		(0.765)		(0.372)	
Cadiz	-0.107	-0.040	-0.034	-0.012	-0.166	-0.062	0.023	0.008
	(0.104)		(0.153)		(0.334)		(0.064)	
Cantabria	-0.050	-0.019	0.025	0.009	0.187	0.072	-0.105	-0.038
	(0.099)		(0.149)		(0.325)		(0.096)	
CatolicaStVic	0.212**	0.082**	0.160***	0.061***	-0.035	-0.013	0.245	0.093
	(0.095)		(0.059)		(0.198)		(0.320)	
Complu Mad	-0.068	-0.026	-0.142***	-0.052***	-0.422***	-0.151***	-0.031	-0.011
	(0.098)		(0.042)		(0.088)		(0.064)	
Cordoba	-0.234***	-0.085***	-0.206***	-0.074***	-0.502*	-0.177*	-0.075	-0.027
	(0.030)		(0.023)		(0.304)		(0.127)	
EuropeaCees	0.005	0.002	0.032	0.012	0.096	0.037	-0.160	-0.057
	(0.109)		(0.133)		(0.186)		(0.119)	
Gerona	-0.121	-0.045	-0.049	-0.018	-0.342	-0.125	0.042	0.015
	(0.106)		(0.168)		(0.253)		(0.135)	
Granada	-0.137	-0.051	-0.114	-0.042	-0.401***	-0.144***	-0.007	-0.002
	(0.088)		(0.093)		(0.098)		(0.102)	
Int Cat	0.147	0.057	0.152	0.058	0.577***	0.219***	-0.247***	-0.086***
	(0.106)		(0.111)		(0.175)		(0.089)	
Laguna	0.019	0.007	0.074	0.028	-0.002	-0.001	0.103***	0.039***
	(0.050)		(0.094)		(0.357)		(0.030)	
Lleida	-0.372***	-0.131***	0.101	0.038	0.826	0.303	-0.196	-0.069
	(0.106)		(0.508)		(0.711)		(0.452)	
Malaga	-0.197	-0.072	-0.134	-0.049	-0.191	-0.071	-0.116	-0.041
	(0.178)		(0.230)		(0.415)		(0.208)	
Murcia	-0.024	-0.009	0.222	0.085	0.388	0.149	0.144	0.054
	(0.129)		(0.317)		(0.362)		(0.302)	
Navarra	-0.032	-0.012	0.005	0.002	-0.029	-0.011	0.011	0.004
	(0.103)		(0.131)		(0.204)		(0.126)	
Oviedo	-0.338**	-0.120**	-0.302*	-0.106*	-0.554	-0.193	-0.204*	-0.072*
	(0.151)		(0.168)		(0.357)		(0.122)	
Pais Vasco	-0.059	-0.022	-0.122	-0.044	-0.501***	-0.176***	0.001	0.000
	(0.152)		(0.118)		(0.059)		(0.145)	
Rey JC	-0.169	-0.062	-0.097	-0.036	-0.172	-0.064	-0.071	-0.026
	(0.106)		(0.168)		(0.246)		(0.136)	
Salamanca	-0.104**	-0.039**	0.049	0.018	-0.039	-0.015	0.101	0.038
	(0.049)		(0.149)		(0.126)		(0.186)	
Santiago	-0.202*	-0.074*	-0.066	-0.024	-0.050	-0.019	-0.074	-0.027
	(0.115)		(0.232)		(0.227)		(0.229)	
Sevilla	-0.060	-0.023	-0.106*	-0.039*	-0.164	-0.061	-0.090***	-0.033***
	(0.099)		(0.059)		(0.179)		(0.017)	
Tarragona	0.018	0.007	-0.164**	-0.059**	-0.304***	-0.111***	-0.112*	-0.040*
	(0.142)		(0.080)		(0.100)		(0.067)	
UB BCN	0.012	0.004	-0.001	-0.000	0.104	0.040	-0.021	-0.008
	(0.109)		(0.095)		(0.242)		(0.041)	
ULPGC	-0.269	-0.097	-0.241	-0.086	-0.656	-0.222	-0.070	-0.025
	(0.301)		(0.313)		(0.472)		(0.233)	
Valencia	-0.022	-0.008	-0.050	-0.019	-0.335***	-0.122***	0.045	0.017
	(0.110)		(0.092)		(0.088)		(0.093)	
Valladolid	0.035	0.013	0.043	0.016	-0.271	-0.100	0.152	0.057
	(0.169)		(0.184)		(0.246)		(0.171)	
Zaragoza	-0.097	-0.036	0.002	0.001	-0.036	-0.014	0.016	0.006
	(0.098)		(0.173)		(0.406)		(0.086)	
Constant	0.959***		0.477		-0.111		0.659	
	(0.275)		(0.655)		(0.714)		(0.564)	
N	6,183		6,183		1,745		4,438	
R^2	0.009		0.009		0.025		0.007	
Log-Likelihood	-3980.402		-3979.754		-1131.163		-2831.942	
AIC	7964.804		7963.508		2266.325		5667.884	

[a] Base outcomes: Gender: Men, Nationality:Non-Spanish, Medical School: Univesidad Autonoma de Barcelona

[b] SE: Standard Errors clustered by MIR year; AME: Average Marginal Effect

[c] P-values: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table 4.9: Estimation results variable y_3

	(1) All Sample		(2) All Sample		(3) Only Men		(4) Only Women	
	β (SE)	AME	β (SE)	AME	β (SE)	AME	β (SE)	AME
Women	-0.660***	-0.232***	-0.658***	-0.231***				
	(0.046)		(0.048)					
Age	-0.011	-0.004	-0.010	-0.004	-0.019**	-0.007**	-0.008	-0.003
	(0.011)		(0.011)		(0.009)		(0.019)	
Spanish	0.048	0.017	0.051	0.018	-0.096	-0.037	0.215	0.072
	(0.217)		(0.221)		(0.265)		(0.237)	
GPA	-0.098	-0.035	-0.099	-0.035	-0.104*	-0.040*	-0.099	-0.033
	(0.103)		(0.103)		(0.053)		(0.135)	
First Mir	-0.077***	-0.027***	-0.079***	-0.028***	-0.372***	-0.142***	0.074	0.025
	(0.013)		(0.013)		(0.091)		(0.065)	
Role Model (RM1)			0.730	0.257	-0.202	-0.077	0.928**	0.309**
			(0.595)		(1.541)		(0.370)	
AUMadrid	0.288***	0.102***	0.256**	0.089**	0.076	0.029	0.416**	0.123**
	(0.085)		(0.105)		(0.139)		(0.194)	
Alcala	-0.121	-0.039	-0.166	-0.052	-0.483***	-0.189***	0.076	0.019
	(0.170)		(0.163)		(0.150)		(0.315)	
Alicante	0.018	0.006	0.078	0.026	0.152	0.057	0.100	0.026
	(0.259)		(0.250)		(0.180)		(0.291)	
Badajoz	0.586***	0.215***	0.771***	0.282***	-0.215	-0.084	1.366***	0.484***
	(0.131)		(0.219)		(0.658)		(0.364)	
CEU	0.977***	0.359***	0.944***	0.345***	0.000	0.000	0.880***	0.296***
	(0.044)		(0.061)		(.)		(0.126)	
CMancha	0.234	0.082	0.694***	0.253***	-0.641	-0.249	1.237***	0.435***
	(0.194)		(0.171)		(1.157)		(0.239)	
Cadiz	-0.042	-0.014	0.035	0.011	-0.333	-0.131	0.261*	0.073*
	(0.091)		(0.044)		(0.353)		(0.142)	
Cantabria	0.423***	0.153***	0.506***	0.182***	0.134	0.050	0.698	0.225
	(0.054)		(0.046)		(0.726)		(0.607)	
CatolicaStVic	0.666***	0.245***	0.612***	0.222***	0.739***	0.238***	0.188	0.051
	(0.071)		(0.083)		(0.114)		(0.788)	
Complu Mad	0.294***	0.104***	0.213***	0.073***	0.163	0.061	0.335***	0.096***
	(0.037)		(0.046)		(0.235)		(0.094)	
Cordoba	0.036	0.012	0.067	0.022	-0.599***	-0.233***	0.389	0.114
	(0.238)		(0.218)		(0.015)		(0.272)	
EuropeaCees	-0.738***	-0.192***	-0.709***	-0.182***	-0.890***	-0.336***	0.000	0.000
	(0.049)		(0.049)		(0.174)		(.)	
Gerona	0.345***	0.123***	0.422***	0.150***	0.000	0.000	0.344***	0.099***
	(0.056)		(0.057)		(.)		(0.107)	
Granada	0.168	0.058	0.193*	0.066*	-0.502	-0.197	0.525**	0.161**
	(0.130)		(0.104)		(0.416)		(0.256)	
Int Cat	-0.186***	-0.059***	-0.182***	-0.056***	-0.222*	-0.087*	0.000	0.000
	(0.048)		(0.043)		(0.135)		(.)	
Laguna	0.211	0.074	0.270	0.094	-0.537	-0.210	0.701*	0.226*
	(0.241)		(0.285)		(0.664)		(0.426)	
Lleida	-1.027***	-0.237***	-0.511	-0.142	-1.190	-0.423	0.000	0.000
	(0.069)		(0.436)		(1.213)		(.)	
Malaga	0.274**	0.097**	0.340***	0.120***	-0.216	-0.084	0.625***	0.197***
	(0.114)		(0.086)		(0.194)		(0.093)	
Murcia	-0.023	-0.008	0.244	0.084	-0.556	-0.217	0.648***	0.206***
	(0.031)		(0.263)		(0.625)		(0.122)	
Navarra	0.202***	0.071***	0.242***	0.084***	-0.122	-0.047	0.439*	0.131*
	(0.076)		(0.045)		(0.300)		(0.224)	
Oviedo	-0.016	-0.005	0.020	0.007	-0.070	-0.027	0.125	0.033
	(0.274)		(0.248)		(0.247)		(0.323)	
Pais Vasco	0.123	0.042	0.053	0.018	-0.131	-0.051	0.223	0.061
	(0.120)		(0.182)		(0.371)		(0.178)	
Rey JC	-0.426***	-0.125***	-0.349***	-0.103***	-0.657**	-0.255**	-0.177	-0.040
	(0.075)		(0.078)		(0.266)		(0.157)	
Salamanca	0.147	0.051	0.315***	0.110***	-0.436	-0.171	0.684***	0.220***
	(0.208)		(0.118)		(0.477)		(0.210)	
Santiago	0.281	0.100	0.426	0.152	-0.074	-0.028	0.680**	0.218**
	(0.206)		(0.293)		(0.525)		(0.327)	
Sevilla	0.200***	0.070***	0.150	0.051	-0.180	-0.070	0.394***	0.115***
	(0.066)		(0.108)		(0.356)		(0.150)	
Tarragona	0.293	0.104	0.089	0.030	0.005	0.002	0.270	0.075
	(0.285)		(0.394)		(0.505)		(0.409)	
UB BCN	-0.072**	-0.024**	-0.086**	-0.028**	-0.298**	-0.117**	0.070	0.018
	(0.032)		(0.038)		(0.145)		(0.065)	
ULPGC	0.266	0.094	0.295	0.103	-0.652*	-0.253*	0.699**	0.225**
	(0.288)		(0.310)		(0.374)		(0.318)	
Valencia	0.428***	0.155***	0.397***	0.141***	-0.005	-0.002	0.631***	0.199***
	(0.064)		(0.092)		(0.326)		(0.169)	
Valladolid	0.214**	0.075**	0.222*	0.077*	-0.090	-0.035	0.414*	0.122*
	(0.105)		(0.120)		(0.517)		(0.249)	
Zaragoza	0.050	0.017	0.159**	0.054**	-0.161	-0.063	0.343	0.099
	(0.067)		(0.069)		(0.450)		(0.261)	
Constant	0.416		-0.113		1.526		-1.482	
	(0.535)		(0.962)		(1.644)		(0.923)	
N	2,186		2,186		664		1522	
R^2	0.058		0.058		0.034		0.025	
Log-Likelihood	-1348.335		-1348.072		-442.753		-885.185	
AIC	2700.670		2700.143		889.505		1774.370	

[a] Base outcomes: Gender: Men, Nationality:Non-Spanish, Medical School: Univesidad Autonoma de Barcelona

[b] SE: Standard Errors clustered by MIR year; AME: Average Marginal Effect

[c] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 4.10: Differences in ranking position by gender: MIR 2013

MIR 2013	Men						Women						Student's t-test				Wilcoxon Rank-Sum	
Ranking	N	Share	$RankDif_M$	SD	Min	Max	N	Share	$RankDif_W$	SD	Min	Max	$\Delta RankDif$	95% CI		t	PR^a	z
< 500	211	10.0%	36.5	103.7	-303	451	288	6.8%	5.2	104.1	-362	313	31.29***	12.79	49.78	3.32	0.582***	3.15
$[500, 1000)$	166	7.9%	50.8	195.5	-454	528	334	7.9%	23.7	173.6	-599	568	27.08	-8.15	62.32	1.51	0.536	1.315
$[1000, 1500)$	162	7.7%	5.4	235.4	-753	534	338	8.0%	8.8	220.8	-762	585	-3.38	-46.77	40.01	-0.15	0.502	0.059
$[1500, 2000)$	168	8.0%	50.0	278.2	-703	770	332	7.8%	12.9	256.5	-691	628	37.09	-13.41	87.59	1.45	0.541	1.498
$[2000, 2500)$	149	7.1%	42.4	337.2	-1277	744	351	8.3%	-6.3	268.3	-978	612	48.76	-12.54	110.06	1.57	0.565**	2.31
$[2500, 3000)$	150	7.1%	75.9	290.8	-857	775	350	8.3%	-14.3	317.7	-1194	718	90.20***	32.76	147.64	3.09	0.579***	2.799
$[3000, 3500)$	173	8.2%	-15.2	341.7	-1329	614	327	7.7%	-5.2	295.2	-1327	713	-10.01	-70.38	50.37	-0.33	0.503	0.105
$[3500, 4000)$	154	7.3%	16.2	290.5	-897	562	346	8.2%	-48.3	294.8	-1390	481	64.52**	8.89	120.14	2.28	0.575***	2.674
$[4000, 4500)$	165	7.8%	-42.7	287.8	-1024	349	335	7.9%	-14.3	241.6	-1390	392	-28.43	-79.62	22.75	-1.09	0.489	-0.413
$[4500, 5000)$	170	8.1%	-21.2	246.8	-1238	359	330	7.8%	-12.7	201.2	-1161	355	-8.51	-51.67	34.66	-0.39	0.52	0.751
$[5000, 5500)$	154	7.3%	-22.1	160.1	-671	272	346	8.2%	-8.5	151.1	-750	261	-13.58	-43.59	16.42	-0.89	0.48	-0.72
$[5500, 6000)$	160	7.6%	-3.7	129.2	-431	184	340	8.0%	1.0	121.2	-581	199	-4.71	-28.62	19.20	-0.39	0.496	-0.158
≥ 6000	124	5.9%	-34.8	117.7	-651	122	225	5.3%	-15.4	85.3	-350	127	-19.44	-43.12	4.24	-1.62	0.468	-0.982
Total	2,106	100%	11.4	246.3	-1329	775	4,242	100%	-5.7	227.1	-1390	718	17.06***	4.51	29.61	2.67	0.526***	3.394

[a] $PR = Pr(RankDif_M > RankDif_W)$

[b] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 4.11: Differences in ranking position by gender: MIR 2013-Spanish sample

MIR 2013	Men						Women						Student's t-test				Wilcoxon Rank-Sum	
Ranking	N	Share	$RankDif_M$	SD	Min	Max	N	Share	$RankDif_W$	SD	Min	Max	$\Delta RankDif$	95% CI		t	PR^a	z
< 500	184	13.8%	31.5	94.2	-303	451	273	8.0%	5.5	101.8	-362	313	26.02***	7.78	44.27	2.803	0.575***	2.707
$[500, 1000)$	134	10.0%	39.2	176.5	-370	494	304	8.9%	23.2	174.2	-599	568	15.92	-19.98	51.82	0.873	0.521	0.699
$[1000, 1500)$	115	8.6%	29.4	203.8	-543	375	293	8.5%	11.6	210.3	-762	585	17.77	-26.83	62.38	0.785	0.529	0.921
$[1500, 2000)$	109	8.2%	19.2	255.1	-649	664	288	8.4%	17.1	241.3	-648	526	2.11*	-53.66	57.88	0.075	0.507	0.21
$[2000, 2500)$	96	7.2%	18.9	322.5	-1277	588	294	8.6%	4.1	251.1	-978	612	14.76	-56.48	86.01	0.410	0.525	0.741
$[2500, 3000)$	93	7.0%	73.0	243.7	-697	483	271	7.9%	-18.4	279.0	-1096	571	91.42***	31.38	151.46	3.005	0.594***	2.706
$[3000, 3500)$	90	6.7%	30.0	268.6	-1260	589	260	7.6%	25.8	245.5	-722	560	4.19	-59.35	67.73	0.131	0.516	0.444
$[3500, 4000)$	99	7.4%	76.5	225.8	-838	485	275	8.0%	0.4	248.0	-1144	481	76.05***	22.44	129.67	2.798	0.6***	2.937
$[4000, 4500)$	95	7.1%	10.5	255.6	-1024	320	263	7.7%	32.1	171.1	-807	346	-21.60	-77.55	34.34	-0.764	0.516	0.457
$[4500, 5000)$	88	6.6%	17.6	201.4	-684	324	252	7.4%	9.3	156.8	-798	324	8.24	-38.54	55.02	0.349	0.555	1.536
$[5000, 5500)$	81	6.1%	21.3	112.0	-328	225	275	8.0%	22.0	102.8	-312	233	-0.76	-28.28	26.75	-0.055	0.509	0.256
$[5500, 6000)$	88	6.6%	22.3	99.6	-291	169	241	7.0%	29.6	84.0	-538	166	-7.32	-30.89	16.25	-0.614	0.489	-0.299
≥ 6000	63	4.7%	-4.3	68.9	-320	75	138	4.0%	8.9	56.5	-316	115	-13.16	-32.85	6.53	-1.326	0.442	-1.321
Total	1,335	100.0%	31.0	206.1	-1277	664	3,427	100%	13.2	197.1	-1144	612	17.80***	4.92	30.68	2.709	0.53***	3.268

[a] $PR = Pr(RankDif_M > RankDif_W)$

[b] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 4.12: Differences in ranking position by gender: MIR 2015

MIR 2015	Men						Women						Student's t-test				Wilcoxon Rank-Sum	
Ranking	N	Share	$RankDif_M$	SD	Min	Max	N	Share	$RankDif_W$	SD	Min	Max	$\Delta RankDif$	95% CI		t	PR^a	z
< 500	234	11.3%	18.2	88.2	-240	292	265	6.7%	23.4	98.6	-231	555	-5.18	-21.61	11.25	-0.619	0.509	0.354
$[500, 1000)$	203	9.8%	71.4	220.1	-538	658	297	7.5%	28.3	192.9	-482	670	43.15**	5.65	80.64	2.262	0.56**	2.264
$[1000, 1500)$	188	9.1%	51.2	280.9	-610	947	312	7.9%	10.9	258.5	-1043	764	40.30	-9.22	89.81	1.600	0.542	1.556
$[1500, 2000)$	158	7.7%	51.2	297.9	-885	732	342	8.7%	-13.6	289.0	-1121	615	64.77**	8.90	120.63	2.282	0.563**	2.26
$[2000, 2500)$	188	9.1%	7.7	300.6	-827	647	312	7.9%	-22.1	289.8	-1198	757	29.75	-24.08	83.59	1.087	0.536	1.345
$[2500, 3000)$	164	7.9%	42.9	308.0	-1119	772	336	8.5%	11.4	301.9	-1177	625	31.48	-25.88	88.84	1.080	0.532	1.162
$[3000, 3500)$	163	7.9%	-21.6	376.0	-2188	715	337	8.5%	-17.2	324.7	-1367	633	-4.35	-71.97	63.27	-0.127	0.511	0.405
$[3500, 4000)$	146	7.1%	-22.3	288.2	-1015	482	354	9.0%	-38.8	259.4	-1088	472	16.51	-37.75	70.78	0.599	0.526	0.916
$[4000, 4500)$	132	6.4%	-19.9	260.8	-1344	343	368	9.3%	-17.7	215.6	-1391	472	-2.22	-52.17	47.73	-0.088	0.528	0.956
$[4500, 5000)$	154	7.5%	-32.5	222.7	-1165	367	346	8.8%	-5.3	173.1	-819	337	-27.22	-67.04	12.61	-1.346	0.468	-1.134
$[5000, 5500)$	140	6.8%	-33.8	176.3	-905	246	360	9.1%	-3.9	132.2	-720	262	-29.92*	-62.36	2.51	-1.819	0.457	-1.483
$[5500, 6000)$	186	9.0%	-23.1	130.4	-999	170	314	7.9%	-8.1	94.7	-574	160	-15.01	-36.57	6.54	-1.371	0.481	-0.729
≥ 6000	8	0.4%	-3.8	5.9	-11	3	8	0.2%	-0.3	6.3	-11	8	-3.50	-10.06	3.06	-1.145	0.336	-1.113
Total	2,064	100.0%	10.4	255.1	-2188	947	3,951	100.0%	-5.4	234.1	-1391	764	15.86**	2.65	29.07	2.353	0.522***	2.847

[a] $PR = Pr(RankDif_M > RankDif_W)$
[b] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Table 4.13: Differences in ranking position by gender: MIR 2015-Spanish sample

MIR 2015	Men						Women						Student's t-test				Wilcoxon Rank-Sum	
Ranking	N	Share	$RankDif_M$	SD	Min	Max	N	Share	$RankDif_W$	SD	Min	Max	$\Delta RankDif$	95% CI		t	PR^a	z
< 500	224	13.5%	18.9	89.0	-240	292	259	7.3%	23.8	98.4	-231	555	-4.99	-21.74	11.77	-0.585	0.510	0.388
$[500, 1000)$	177	10.6%	76.6	211.5	-538	658	278	7.8%	32.3	189.7	-482	670	44.32**	5.88	82.77	2.268	0.564**	2.316
$[1000, 1500)$	160	9.6%	55.8	261.0	-610	660	294	8.2%	17.0	258.2	-1043	764	38.82	-11.44	89.09	1.520	0.545	1.583
$[1500, 2000)$	131	7.9%	48.3	277.9	-677	732	317	8.9%	-4.7	281.6	-1121	615	52.99*	-4.09	110.07	1.829	0.543	1.446
$[2000, 2500)$	144	8.7%	48.1	261.2	-667	647	280	7.8%	-14.4	265.5	-987	597	62.43**	9.41	115.44	2.318	0.567**	2.254
$[2500, 3000)$	129	7.8%	36.3	297.2	-1119	618	308	8.6%	34.3	279.9	-1177	625	2.00	-58.38	62.38	0.065	0.513	0.414
$[3000, 3500)$	123	7.4%	27.6	363.0	-2188	715	301	8.4%	15.1	294.3	-1367	633	12.42	-60.29	85.14	0.337	0.535	1.144
$[3500, 4000)$	112	6.7%	8.2	261.0	-765	387	317	8.9%	-10.6	234.7	-1088	472	18.84	-36.34	74.02	0.674	0.533	1.038
$[4000, 4500)$	109	6.6%	3.2	245.8	-1344	311	336	9.4%	-1.7	183.3	-1120	472	4.94	-45.60	55.47	0.193	0.546	1.447
$[4500, 5000)$	129	7.8%	-18.2	218.5	-1165	274	313	8.8%	9.0	149.2	-819	288	-27.20	-68.66	14.25	-1.295	0.475	-0.815
$[5000, 5500)$	101	6.1%	12.9	93.3	-281	246	319	8.9%	16.1	101.7	-517	262	-3.21	-24.70	18.28	-0.295	0.477	-0.707
$[5500, 6000)$	118	7.1%	7.7	73.4	-369	170	244	6.8%	13.2	72.1	-574	160	-5.55	-21.68	10.58	-0.678	0.481	-0.574
≥ 6000	7	0.4%	-4.7	5.6	-11	3	6	0.2%	-2.7	5.2	-11	3	-2.05	-8.71	4.61	-0.678	0.393	-0.649
Total	1,664	100%	29.5	233.3	-2188	732	3,572	100.0%	10.3	216.7	-1367	764	19.18***	5.90	32.45	2.832	0.528***	3.278

[a] $PR = Pr(RankDif_M > RankDif_W)$

[b] P-values: $***p < 0.01, **p < 0.05, *p < 0.1$

Chapter 5

Conclusion

This thesis has presented analysis of the influence of doctors' sociodemographic characteristics on their medical specialty allocation outcomes. The findings identify and quantify disparities across specialties and locations in the UK and the Spanish health systems. We also explore the channels through which those differences arise and are transmitted. These findings can assist policy makers and regulators to better design and target workforce planning and recruitment strategies and hence make better use of resources to improve access to care and the efficiency in health service delivery.

The priorities regarding health workforce have shifted from broad concerns about widespread shortages to more specific issues such as the existence of large imbalances across specialties and/or locations (OECD 2016). Examples of those imbalances are the over-subscription of some specialties, the increasing recruitment problems in others, especially in general practice, and the under-supply of doctors in rural areas. Such imbalances are closely linked to the major changes observed in the composition of the medical workforce in the last two decades: the feminization of the profession, the increased representation of ethnic minority doctors and those coming from deprived socioeconomic backgrounds, and the increased reliance on foreign-graduated doctors. The influence of these factors is explored throughout this thesis.

The findings from Chapter 2, that constitutes a descriptive exercise of the socio-demographic composition of the new cohorts of doctors in the UK, show that incumbent groups in the profession (i.e. young, white, male, and from a socioeconomic privileged background doctors) are still overrepresented in the most demanded specialties. The latter have been historically associated with larger earnings and other non-pecuniary attributes such as prestige or peer recognition. Female doctors, who are now the largest group of doctors in training, are more likely to be allocated to primary care specialties that are characterized by being in low demand and more poorly remunerated than high-demand specialties. Similarly, we find that foreign-graduated doctors, who in most cases are the best doctors from their country of origin (Tsugawa, Jena, Orav et al. 2017), are crowded into the less popular specialties and locations. The latter comes at the risk of creating an underclass of doctors within the health system as it might entail a lower quality of training and working experience for those doctors.

The achievement of an equal distribution of doctors across specialties is desirable not only from an equity perspective. There are economic aspects associated with the unequal sorting such as earning disparities between groups, one example being the gender wage gap. [41] Unequal sorting of doctors can also lead to large differences in productivity across specialties as there is evidence that females have lower activity rates than male doctors (Bloor et al. 2008) and they tend to work fewer hours than males (Simoens and Hurst 2006). Similarly, unequal sorting can lead to large differences in quality of care across specialties as there are documented differences between male and female doctors in communication styles (Cooper-Patrick et al. 1999), compliance with guidelines (Baumhäkel et al. 2009) and mortality and readmission rates (Wallis et al. 2017; Tsugawa, Jena, Figueroa et al. 2017). A more equal distribution of doctors might equalise those differences across specialties and heighten the quality of care in the system as a whole.

We also find *geographical* imbalances in the distribution of doctors since female doctors and doctors from better-off socioeconomic backgrounds have higher degrees of aversion to geographical mobility to low-demand locations. One major policy concern is filling training positions in general practice in rural areas, because females who are more likely to be training in general practice are also less likely to choose a rural area. Therefore, encouraging a more equal distribution of doctors in general practice with respect to gender could mitigate geographical shortages.

Chapter 2 also sets out several potential reasons for observed differential attainment and disentangling between those motivates the analysis of Chapters 3 and

[41] The gender wage gap has grown over the past decade in the UK (Rimmer 2017) and those differences are likely to be explained by the different specialty choices between the two groups (Arcidiacono and Nicholson 2005)

4. A traditional explanation is that occupational segregation reflects differences in intrinsic preferences between groups regarding different specialties' pecuniary and non-pecuniary attributes. If that were the sole reason, then there would be little scope for policy action. Alternatively, differential attainment may arise from information asymmetries. Stereotypes and preconceptions associated with specific groups can affect doctors' self-assessments of their perceived probabilities of success (i.e. gaining access to their preferred training post), lead them to wrong judgements and negatively affect their skill investments. A lower level of skill investments would diminish their real probabilities of success and as a consequence lead them to a self-fulfilling prophecy.

The conceptual framework in Chapter 3, that analyses the functioning of the two-sided allocation process in the UK and establishes the channels by which doctors' characteristics influence their choices and selectors' valuations, accounts for doctors' own perceptions and beliefs as a determinant of their application behaviour. The Probit estimation results show that the observed specialty allocation outcomes in Chapter 2 are largely driven by doctor application choices, even after controlling for educational background and attainment. Nevertheless, the UKMED data utilised does not allow us to identify whether those choices are driven by intrinsic differences in preferences between groups, or arise from differences in the perceived probability of gaining access to the most-demanded specialties. We conjecture that the latter is likely to play an important role in the decision-making process of many individuals, as Goldacre et al. (2010) finds large mismatches between early specialty choices and eventual career destinations of UK doctors and Soethout et al. (2004) in a literature review of European studies find that self-appraisal of skills constitutes one of the main factors associated with specialty choice.

The analysis of the factors influencing the total number of applications sheds light on doctors' perception of success. The results show that BME and older doctors are more likely to submit multiple applications even after controlling for specialty fixed effects. We conjecture that individuals who make a unique application might be reflecting a higher degree of self-confidence, will devote more time and resources to prepare the application and interview processes and as a result will have a higher probability of receiving an offer. The estimates from the selection stage confirm the latter, as making more than one application has a negative effect on interview scores.

Information asymmetries might be also present in the selection process when selectors have imperfect information about the candidates they need to evaluate. In that instance, they may rely on historical rates of success from the socio-demographic group the candidate belongs to, and hence they would use group identity as proxy for unobserved characteristics. Alternatively, selectors can simply suffer from unconscious biases that are based on stereotypes and preconceptions. In Chapter 3, we also analyse the determinants of selectors' valuations of candidates and focus on identifying whether the source of differences in interview scores between groups can be explained by their differences in endowments, or by contrast remain unexplained and can be associated to discrimination. Our findings for UKMED doctors corroborates past evidence on differential attainment of ethnic minority doctors and male doctors. We find strong evidence of BME doctors scoring less highly than white doctors in the interview that is pivotal in giving access to a speciality training position. We also find that female doctors score more highly than male doctors. The results show that on average two thirds of the gap in interview score between white and ethnic minority doctors remains unexplained. With respect to gender, the gap in the interview score is smaller, favouring females, however with the special feature that the explained effect favours male doctors whilst the unexplained is negative for male doctors. Therefore, it seems that despite all the measures implemented to ensure a fair and transparent recruitment process (General Medical Council 2010), the interview process might be prone to some bias.

Entry barriers to high demand specialties are another source of differential attainment, and those might be more pronounced for doctors who belong to historically deprived groups. Entry barriers can be *real* such as financial constraints (oversubscribed specialties often require of higher skills investments), limited access to professional networks, nepotism, incompatibilities between specialty training schedules and doctors' personal schedules, etc. The results from the application stage in Chapter 3 show that female doctors self-select into low-income specialties and away from high-income specialties, whilst younger and ethnic minority doctors[42] and those coming

[42]Ethnic minority doctors in our sample come from wealthier backgrounds than the average doctor. That can partially explain their leaning toward high-income specialties.

from better-off socioeconomic backgrounds are more likely to apply to high-income specialties. This situation is likely to exacerbate the gender wage gap in the profession and perpetuate inequities in the distribution of wealth among socioeconomic groups. Moreover, females and older doctors are more likely to select themselves into run-through/primary care specialities, that on average have shorter training periods and only require going through the specialty allocation process once. It might be easier to work on a part-time basis when training for a run-through specialty and therefore these might be preferred by doctors looking for a better work-leisure-family balance.

Entry barriers can also be *perceived* and therefore closely related to the role of stereotypes and preconceptions affecting doctors' skills investments, as described above, or to the lack of role models from the same demographic group. In Chapter 4, that focuses on the Spanish resident physician market, we analyse the role of social interactions in shaping doctors' decisions to specialize. We analyse whether the lack of same sex role models is perceived as an entry barrier by female doctors. We find that being exposed to female role models, who are female junior doctors training in surgical male-dominated specialties, increases the probability of choosing a male-dominated surgical specialty, with respect to any other specialization, of both men and women. When the analysis is restricted to the sample of doctors with an interest in surgical specialties the role model effect is only statistically significant for female doctors. Nonetheless, our findings suggest that the role model variable might be capturing other elements affecting decisions to specialize. Moreover, the estimation of social interactions is very challenging and it is something that might or might not occur when females are better represented among surgical specialties (Neumark and Gardecki 1996).

Finally, the differential attainment might also come from the design of the specialty allocation process as its features might favour one group over the others. Results from Chapter 4 show the effect of policy change that increased the competitiveness of the Spanish specialty allocation process. The objective of the change was to ensure the objectivity of the process by increasing the weight of an examination score in detriment to the weight associated with previous attainment in medical undergraduate studies, as regulators see the latter as more prone to biases. We find that the policy change had the unintended consequence of reducing the ranking scores from female doctors and hence lowering their probability of accessing the most demanded specialties. We conjecture that the well-documented gender gap in competitiveness (Frick 2011) might be the main driver of the differences.

The findings from this thesis provide evidence of the occupational segregation of the new cohorts of doctors in training in UK and Spain and discriminate between competing explanations for those differences. Therefore, the findings can be taken as a road map for policy makers to address the current policy concerns.

To tackle imbalances, the main objective should be promoting a balanced representation of female doctors across specialties. Our evidence shows that female doctors' differential attainment takes place in the application stage, as they self-select themselves into low-income specialties and away from high-income specialties that have associated lower levels of non-pecuniary benefits.[43] It is unclear whether this sorting is driven by differences in intrinsic preferences with respect to income between the two groups or whether the lower levels of non-pecuniary benefits constitute a real entry barrier for some women. In the latter case, policies which aim to make male-dominated specialties more attractive should focus on improving the non-pecuniary benefits associated with them. In addition, policies should focus on eliminating perceived entry barriers in those specialties where females are underrepresented. Our findings regarding the female role model effect are not conclusive but, they do suggest that increasing the number of visible figures constitutes an attractor factor. Therefore, if the objective is to lessen the specialty gender segregation, incentivising mentoring programmes and giving more visibility to role models might meet the goal.

Other policy concerns are ensuring balance in the profession with respect to doctors' ethnicity, as well as ensuring a fair and transparent recruitment process (General Medical Council 2010). To improve representation and tackle imbalances, the aim should be to improve the attainment in the specialty process of ethnic minority doctors. They show differential attainment in the selection stage, partly due to their less effective application strategies and partly to their worse interview outcomes that cannot be fully explained by differences in observable characteristics between them and white doctors. A policy action could be to provide more guidance on how to tackle

[43]Example of non-pecuniary benefits are flexibility to work part time, working hours that are more compatible with family life or that allow for a work-leisure balance

the application stage.[44] Moreover, the selection stage needs to be examined carefully to identify the elements that are driving the *unexplained* differences in interview scores.

The findings from this thesis also shed light on how to tackle the current recruitment crisis in general practice.[45] For example, around 18% of training places in England were unfilled after two rounds of recruitment (Pulse Today 2017) and the recruitment problem is even more pronounced in low-demand areas, such as the North East, East Midlands and Yorkshire, where over a third of the posts remained unfilled (Rimmer 2015). One policy remedy to the crisis can be increasing the number of male general practitioners. Our findings show that male doctors are more likely to apply to high-income specialties, then financial incentives might attract them to the field and help mitigating the shortages in rural areas as, they are also more likely than females to be training in the low-demand locations.

Increasing the medical school intake is seen as one of the main policy remedies to the GP shortage according NHS Forward View Plan (NHS England 2014). Nonetheless, our findings show that doctors from privileged socioeconomic backgrounds, who are the largest group in the profession, are less likely to apply to general practice. Then, the objective should not only be to increase the school intake, but also to democratise the medical profession by giving access to students from less socioeconomic-privileged backgrounds. Moreover, it will be worth investigating whether doctors from privileged socioeconomic backgrounds specialising in the most profitable specialties are more likely to work for the private sector and therefore reduce their effort in the public sector. [46] The exodus of that group to the private sector might lead to shortages of doctors, longer waiting lists and to an overall a reduction in the productivity of the NHS.

In addition, not only is an increase in the intake of medical students needed, but also a better understanding of the role of medical schools in shaping doctors preferences

[44] If in reality making more applications, implies producing lower quality applications, BME doctors should be encouraged to apply wisely and focus their efforts on one option.

[45] The ageing of the general population and the increasing number of general practitioners close to retirement age put pressure on the health care system and there is the need to increase the number of general practitioners. In particular in the UK, the objective is to increase the number of GPs by 5000 by 2020 (NHS England 2014).

[46] Doctors from privileged socioeconomic backgrounds might have better professional networks, be more likely to be able to afford the costs of opening a surgery or, in general, may feel less identification with the values of the NHS with respect to those coming from worse-off socioeconomic backgrounds.

is required. Goldacre et al. (2004) found significant differences in specialty choices between doctors from different medical schools whilst our findings show that the 'medical school effect' has significant influence in doctors' application strategies. There are some medical schools, such as Birmingham, whose students are more likely to choose general practice as their career choice. From a policy perspective, isolating the medical school effect in specialty choice from other elements, such as each doctor's ability, role of networks, etc., can be highly informative to the design of a medical curriculum that emphasises the importance and attractiveness of general practice.

In synthesis, the main goal of policy makers should *not* be to ensure an exact distribution of the different socioeconomic groups of doctors across specialties, but to examine the allocation process and work towards the elimination of any entry barriers, *perceived* or *real*, in order to ensure the equity of access to an activity funded with taxpayers' money. Achieving the latter would offer, productivity and quality gains and therefore optimise the resources from the Health System.

5.1 Limitations and further research

Whilst the strengths from this thesis have been explained in detail in the introductory chapter, this research is also subject to a number of limitations.

Chapter 2 examines the distribution of doctors across specialty and locations separately, whilst Chapter 3 focus on the impact of doctors' sociodemographic characteristics in their specialty application patterns, but does not study how those characteristics affect location. Nonetheless, these two elements are interdependent and the analysis of the trade-off existing between doctors' desired specialty and desired location constitutes a promising avenue for future research. The latter can be done by comparing doctors' desired specialty and location with their actual choices as in Harris et al. (2017). Alternatively, that trade-off can be examined through a discrete choice experiment. The latter would also allow exploring how specialty attributes, such as expected hours of work or expected income, are related to doctors' personal characteristics. That knowledge could lead to better recruitment strategies as it will provide a better understanding of the mechanisms leading to the current geographical and specialty imbalances.

In Chapter 2, we observe that foreign graduated doctors are more likely to be training in low-demand specialties and locations. However, as UKMED data only includes information from doctors who graduated in the UK, we were not able to analyse their application strategies or their attainment in the selection stage. Given that over one quarter of doctors in training graduated overseas, further research should analyse whether crowding them into the less demanded training posts means that they receive a poorer quality of training and examine the possible consequences of the latter on patient outcomes.

One of the most important elements from the conceptual framework in Chapter 3 is the distinction between the intrinsic benefit associated to the practice of a specialty and the perceived probability of entering that specialty. However, UKMED data does not allow the identification of both effect separately. Further research could focus on identifying information asymmetries between the sociodemographic groups and disentangling the effect of perceived probability and net benefit in specialty choices by comparing the divergences between doctors' stated preferences and actual application choices. The identification of those divergences will help in the design of targeted policy actions aim to redress them.

Another avenue of research is identifying the sources of the unexplained differences in interview scores between demographic groups. As a first step, the analysis of inequities should go beyond the mean, following the work of Firpo et al. (2009) and Chernozhukov et al. (2013), by testing whether the gap in interview score is greater or smaller in other parts of the interview score distribution. Moreover, further research should have access to further releases of UKMED data leading to larger sample sizes that will test the generalisability of our findings.

The estimation results on how female role models affect female doctors' decisions to specialise in Chapter 4 are not conclusive. The estimation of social interactions is very challenging and further research should have access to better data and look into see what forms of mentoring might be the most productive. Moreover, social interactions have an important role in specialty choice decisions and can take multiple forms. A further promising and challenging avenue of research can be the identification of endogenous effects, such as the propensity of medical students to vary their behaviour towards specialty choices with the behaviour of their peers.

Chapters 3 and 4 analyse the determinants of sociodemographic occupational segregation in the medical workforce for two countries with very different specialty allocation systems. The findings show that both systems have flaws and we conjecture that a hybrid specialty allocation system, that combines a test like the MIR examination and an interview process, could reduce the ethnic (and gender) biases observed for the UK system and be more accountable of the skills that are required of modern doctors in the Spanish system. Future research could focus on an analysis of different types of specialty allocation systems. The analysis should include the estimation of operational[47] costs as well as doctors' private[48] costs associated with each of the allocation systems, and compare the efficiency and equity of the resulting allocation of doctors across specialties and locations.

[47]In the UK, those are the logistic costs of organizing interviews, shortlisting and initial screening processes. In the case of Spain those cost are associated to setting a centralised exam.

[48]Those are private opportunity costs borne by doctors who take part in the specialty allocation process. Those are likely to be larger in Spain than in the UK as the typical medical student needs at least six-months of full-time preparation for the MIR examination. Nonetheless, getting access to highly-demanded specialties in the UK requires skill investments that need to be made long before the moment of specialty allocation and might be also associated with high opportunity costs.

Chapter 6

Appendices

6.1 Appendix to Chapter 2

Results location

Chapter 2 focuses on the distribution of doctors across specialties. Nonetheless, we also explore the relationship between doctors' sociodemographic characteristics and the geographical location they are training for. The NTS includes the variable trust name that informs about the *Location* where doctors carry out the specialty training. We associate each trust to the corresponding Local Education and Training Board (LETB) and group those into six categories, taking into account those LETBs that are close enough and might be perceived as substitutes by doctors. The resulting locations are:

- East of England, East and West Midlands (MID)
- London (LON)
- Thames Valley and Kent Surrey and Sussex (TVKSS)
- South West Peninsula, South West Severn and Wessex (SOU)
- North East, North West Mersey, North West North Western and Yorkshire and the Humber (NOR)
- North Ireland, Scotland, Wales and Military (OTH)

There were 147 observations for which trust name was unspecified and therefore the *General sample* and the *UK sample* include less observations with respect to the analysis for *specialty*, 27,383 and 19,290 respectively.

For interpretation purposes, we classify the six alternatives into *high-demand* and *low-demand* as Table 2.3 sets out. The classification is based on average competition ratios, given by the number of applications divided by the number of training posts, from the different specialties/locations for the years 2012-2015. Each year, on average, the number of applications submitted by doctors is double the number of training posts. Therefore, we define alternatives with historical competition ratios lower than two as *low-demand* and those with a competition ration greater than two as *high-demand*.

6.1.1 Descriptive statistics

General sample

Table A2.1 shows the descriptive statistics for the *General sample* regarding the geographical distribution of doctors in training. The descriptive statistics suggest that the distribution of doctors across locations is highly unequal. The percentage of male and female doctors in the *General sample* is 45.54% and 54.46%, respectively. However, women are underrepresented in MID (50.02%) and NOR (51.31%) and overrepresented in LON (60.72%). With respect to ethnicity there are also large disparities, the overall percentage of BME doctors is 41.17% whilst the lowest percentage corresponds to SOU (19.35%) and the largest to MID (58.39%). The overall percentage of *Mature* doctors in the *General sample* is 5%, the smallest representation of them is found for SOU (3.27%) and the largest for LON (6.83%). Finally, regarding the place of medical qualification, 24.41% of doctors qualified in an overseas medical school. The largest representation of overseas doctors is observed in MID (33.77%) and the smallest in SOU (13.74%) and LON (17.92%).

UK sample

Table A2.2, concerns the *UK sample* that includes the additional socioeconomic variables. In this group the percentage of *Women* (58.36%) is greater than in the *General sample*, suggesting that non-UK educated doctors are more likely to be male. Moreover, the geographical distribution of female doctors is similar to the observed for the *General sample*. The percentage of *BME* doctors is substantially smaller (25.32%) in this sample and the distribution of BME doctors across locations is highly unbalanced. The largest representation can be found in MID (40.52%) and LON (40.08%) whilst the smallest in SOU (9.75%) and OTH (6.8%). Similarly, the percentage of *Mature* doctors is significantly smaller (1.33%) than the one observed for doctors in the *General sample* and their distribution across specialties is fairly similar.

The *UK sample* also includes information on socioeconomic variables. Overall, doctors have attended an *Independent* school in a larger proportion (35.31%) than the general UK population (approximately 7%). Moreover with regard to the geographical distribution, doctors from *Independent* schools are overrepresented in England compared to the rest of the UK, represented by the category OTH (23.65%); within England, LON is the region with a largest representation of *Independent* school doctors (44.92%) whilst NOR shows the smallest (32.11%). We observe the opposite for *State* school with the largest representation of doctors in NOR (43.55%) and OTH (43.28%) and the smallest in LON (32.43%). The other socioeconomic variable present in the data is *Parent uni*, and the percentage of doctors with at least one parent with tertiary education is 65.8%. Doctors in training in NOR show the smallest percentage for *Parent uni* (62%), whilst those in LON show the largest (71.76%).

6.1.2 Estimation results

General sample

Table A2.3 shows the mixed logit estimation results for the *General sample*. For each alternative the estimate associated with each covariate (MLE) and the corresponding odds ratio (OR). The omitted alternative is MID as the region is in the centre of the UK and comprises the largest number of doctors in training.

The variable *Men* is negative and statistically significant for LON and TVKSS at the 99% and 90% confidence levels. A male doctor is on average 29% (OR 0.71) and 12.9% (OR 0.871) less likely to be based in LON and TKVKSS, respectively. By contrast, a male doctor is 1.62 and 1.66 times more likely than a female doctor to be located in NOR and OTH with respect to MID. The estimates for the variable BME are all negative and statistically significant at the 99% confidence level. MID is the region where a BME doctor is more likely to found in specialty training, whilst a

BME doctor is on average 84.9% (OR 0.15) and 94.3% (OR 0.06) less likely to be in training in SOU and NOR, respectively. The MLE for the variable *Mature* is only statistically significant at the 95% confidence level for LON, where it is 1.273 times more likely that a Mature doctor is in training with respect to MID. Finally, the variable *UK university* is statistically significant for all alternatives with respect to the base outcome. The estimates are positive for LON, TVKSS and SOU, where doctors who graduated in the UK are 2.12, 1.34 and 1.43 times more likely to be training there, with respect to the base outcome. By contrast, UK graduates are less likely to be based in NOR and OTH.

UK sample

Table A2.4 shows the mixed logit estimation results for the *UK sample*. As for the *General sample* MID is the omitted alternative. For this sample, the effect of the variable *Men* is only statistically significant for LON (OR 0.066) and TVKSS (OR 0.83). Moreover, as for the *General sample* the estimates associated with the variable BME are negative for all alternatives and also statistically significant with the exception of LON. The estimates for the variable *Mature* are no longer statistically significantly different from zero.

With regard to the socioeconomic variables, the estimates for *Independent* school are positive and statistically significant for LON and TVKSS. We find that doctors from better-off socioeconomic backgrounds are 1.79 and 1.47 times more likely to be based in LON and TVKSS than in MID. A negative and statistically significant effect is found for OTH (OR 0.21). Results for *grammar* school are all positive and statistically significant for all alternatives with the exception of NOR. Finally, the estimates for the variable *Parent Uni* are all statistically significant and positive, with the exception of NOR. The largest effects are found for SOU and OTH where doctors who have parents with tertiary education are 1.74 and 1.83 times more likely to be in specialty training in those locations, with respect to MID.

6.1.3 Discussion

The results for location show that with respect to doctors' sociodemographic characteristics there are substantial differences across locations. Doctors training in the most demanded locations, i.e. with the greater competition ratios, are more likely to be female, white, have attended an independent or grammar school, have a parent with tertiary education and have attended a UK university. By contrast, doctors training in NOR and MID, the two least demanded locations, are more likely to be male, from an ethnic minority and have graduated overseas.

England seems to rely on overseas graduate doctors more than the other countries in the UK. Doctors are also more ethnically diverse, probably reflecting the fact that, at population level, England has a greater percentage of ethnic minorities in the population. By contrast, the percentage of doctors in training from better-off socioeconomic backgrounds is greater in England than in the rest of the UK and within England those doctors are overrepresented in the South of England (historically high-demanded location). According to Health Service Journal (2017), most of the regions at risk of general practitioner shortage are located in the South of England. The latter connects with the findings for specialty allocation that show that socioeconomically privileged doctors, who seem to prefer being based in the South, are less likely to be training for general practice. In the medium run, making the profession less *elitist* and more accessible and attractive to doctors from all socioeconomic stratum might palliate the shortages in primary care specialties across the UK.

Our analysis is based on final outcomes from the specialty allocation process and we can only conjecture on the mechanisms giving rise to the observed distribution of trainees across locations and specialties. A further understanding of how doctors are sorted across specialties and locations, and the nature of the trade-offs between those two is required. That exercise can motivate policy interventions aimed at reducing the gaps between supply and demand, both geographical and regarding specialties and hence improving medical workforce planning.

Table A2.1: Characteristics of the doctors in the *General sample*

	ALL		**MID**		**LON**		**TVKSS**		**SOU**		**NOR**		**OTH**	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Gender														
Man	12,470	45.54	2,914	49.98	2,071	39.28	970	44.31	1,214	43.65	3,097	48.69	2,204	44.52
Woman	14,913	54.46	2,916	50.02	3,201	60.72	1,219	55.69	1,567	56.35	3,263	51.31	2,747	55.48
Ethnicity														
BME	11,273	41.17	3,404	58.39	2,440	46.28	973	44.45	538	19.35	2,750	43.24	1,168	23.59
White	16,096	58.78	2,423	41.56	2,832	53.72	1,216	55.55	2,243	80.65	3,603	56.65	3,779	76.33
Missing	14	0.05	3	0.05							7	0.11	4	0.08
Age														
40 years old or more	1,400	5.11	398	6.83	263	4.99	110	5.03	91	3.27	339	5.33	199	4.02
Less than 40 years old	25,983	94.89	5,432	93.17	5,009	95.01	2,079	94.97	2,690	96.73	6,021	94.67	4,752	95.98
Place of studies														
UK	20,698	75.59	3,861	66.23	4,327	82.08	1,678	76.66	2,399	86.26	4,470	70.28	3,963	80.04
Overseas	6,685	24.41	1,969	33.77	945	17.92	511	23.34	382	13.74	1,890	29.72	988	19.96

[a] MID: East of England, East and West Midlands; LON: London; TVKSS: Thames Valley and Kent Surrey and Sussex; SOU: South West Peninsula, South West Severn and Wessex; NOR:North East, North West Mersey, North West North Western and Yorkshire and the Humber; OTH: North Ireland, Scotland, Wales and Military.

[b] BME: Black and minority ethnic

Table A2.2: Characteristics of the doctors in the *UK sample*

	ALL		**MID**		**LON**		**TVKSS**		**SOU**		**NOR**		**OTH**	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Gender														
Man	8,032	41.64	1,655	46.86	1,493	37.51	657	42.41	925	40.1	1,797	43.38	1,505	39.81
Woman	11,258	58.36	1,877	53.14	2,487	62.49	892	57.59	1,382	59.9	2,345	56.62	2,275	60.19
Ethnicity														
BME	4,885	25.32	1,431	40.52	1,595	40.08	512	33.05	225	9.75	865	20.88	257	6.8
White	14,393	74.61	2,098	59.4	2,385	59.92	1,037	66.95	2,082	90.25	3,272	79	3,519	93.1
Missing	12	0.06	3	0.08							5	0.12	4	0.11
Age														
40 years old or older	257	1.33	40	1.13	65	1.63	17	1.1	31	1.34	60	1.45	44	1.16
Less than 40 years old	19,033	98.67	3,492	98.87	3,915	98.37	1,532	98.9	2,276	98.66	4,082	98.55	3,736	98.84
School type														
State	7,439	38.56	1,465	41.48	1,166	29.3	488	31.5	880	38.14	1,804	43.55	1,636	43.28
Grammar	4,380	22.71	720	20.39	878	22.06	322	20.79	452	19.59	886	21.39	1,122	29.68
Independent	6,811	35.31	1,206	34.14	1,788	44.92	676	43.64	917	39.75	1,330	32.11	894	23.65
Missing	660	3.42	141	3.39	148	3.72	63	4.07	58	2.41	121	2.95	128	3.38
Parental University														
Yes	12,692	65.8	2,195	62.15	2,856	71.76	1,082	69.85	1,537	66.62	2,568	62	2,454	64.92
No	5,964	30.92	1,198	33.92	998	25.08	404	26.08	707	30.65	1,443	34.84	1,214	32.12
Missing	434	3.28	139	3.93	126	3.17	63	4.06	63	2.73	131	3.16	112	2.97

[a] MID: East of England, East and West Midlands; LON: London; TVKSS: Thames Valley and Kent Surrey and Sussex; SOU: South West Peninsula, South West Severn and Wessex; NOR:North East, North West Mersey, North West North Western and Yorkshire and the Humber; OTH: North Ireland, Scotland, Wales and Military.

[b] BME: Black and minority ethnic

Table A2.3: Mixed Logit regression estimates for the *General sample*: Location

	LON		**TVKSS**		**SOU**		**NOR**		**OTH**	
	MLE	OR	MLE	OR	MLE	OR	MLE	OR	MLE	OR
Men	-0.343***	0.710	-0.138*	0.871	0.0236	1.024	0.482*	1.619	0.508*	1.662
	(-8.65)		(-2.25)		(0.37)		(2.46)		(2.52)	
BME	-0.253***	0.776	-0.470***	0.625	-1.889***	0.151	-2.862***	0.057	-4.210***	0.015
	(-3.48)		(-4.91)		(-9.65)		(-3.81)		(-5.38)	
Mature	0.241**	1.273	0.0123	1.012	0.0730	1.076	-0.492	0.611	-0.369	0.691
	(2.72)		(0.09)		(0.52)		(-1.68)		(-1.17)	
UK university	0.753***	2.123	0.292***	1.339	0.356**	1.428	-1.471**	0.230	-1.698**	0.183
	(14.61)		(3.64)		(2.70)		(-2.86)		(-3.23)	
Constant	-0.333*	0.717	-1.379***	0.252	-0.149	0.862	1.445***	4.242	1.097**	2.995
	(-2.51)		(-3.91)		(-0.39)		(4.88)		(2.69)	
N	27369									
Log-likelihood	-45990.7									

[a] LON: London; TVKSS: Thames Valley and Kent Surrey and Sussex; SOU: South West Peninsula, South West Severn and Wessex; NOR:North East, North West Mersey, North West North Western and Yorkshire and the Humber; OTH: North Ireland, Scotland, Wales and Military.

[b] MLE (mixlogit estimate); OR (odds ratio)

[c] Man vs. woman; BME vs. non-BME (BME: Black and minority ethnic); Mature vs. non-mature (> 40 vs. < 40 years old); UK university vs. overseas educated student.

[d] Z-scores in parentheses: $***p < 0.01$; $**p < 0.05$ and $*p < 0.1$;

Table A2.4: Mixed Logit regression estimates for the *UK sample*: Location

	LON		TVKSS		SOU		NOR		OTH	
	MLE	OR	MLE	OR	MLE	OR	MLE	OR	MLE	OR
Men	-0.415***	0.660	-0.182*	0.834	0.0319	1.032	-0.0165	0.984	0.0883	1.092
	(-8.12)		(-2.06)		(0.13)		(-0.23)		(0.37)	
BME	-0.177	0.838	-1.845**	0.158	-10.74***	0.000	-1.069***	0.343	-11.19***	0.000
	(-0.86)		(-2.78)		(-3.72)		(-5.47)		(-3.80)	
Mature	0.399	1.490	-0.0243	0.976	-0.0671	0.935	0.202	1.224	-0.326	0.722
	(1.84)		(-0.06)		(-0.07)		(0.72)		(-0.34)	
Independent School	0.584***	1.793	0.383**	1.467	-0.801	0.449	-0.148	0.862	-1.540**	0.214
	(10.20)		(3.10)		(-1.64)		(-1.54)		(-3.04)	
Grammar School	0.430***	1.537	0.470***	1.600	0.816*	2.261	-0.0799	0.923	1.138**	3.121
	(5.67)		(3.49)		(2.14)		(-0.80)		(2.94)	
Parent Uni	0.352***	1.422	0.420***	1.522	0.556*	1.744	-0.102	0.903	0.605*	1.831
	(5.78)		(3.98)		(2.11)		(-1.22)		(2.28)	
Constant	-0.0222	0.978	-0.379	0.685	-2.695**	0.068	-0.0480	0.953	-2.094*	0.123
	(-0.07)		(-1.61)		(-2.84)		(-0.12)		(-2.16)	
N	18456									
Log-likelihood	-30814.4									

[a] LON: London; TVKSS: Thames Valley and Kent Surrey and Sussex; SOU: South West Peninsula, South West Severn and Wessex; NOR:North East, North West Mersey, North West North Western and Yorkshire and the Humber; OTH: North Ireland, Scotland, Wales and Military.

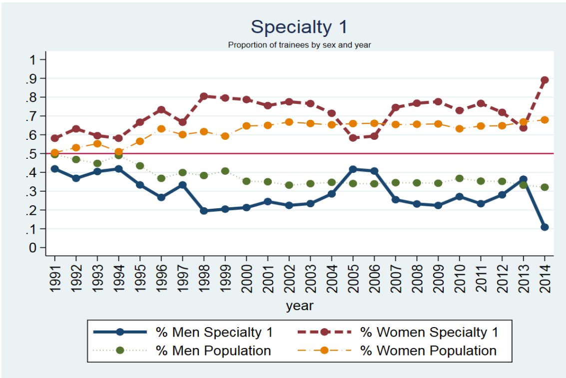
[b] MLE (mixlogit estimate); OR (odds ratio)

[c] Man vs. woman; BME vs. non-BME (BME: Black and minority ethnic); Mature vs. non-mature (>40 vs. <40 years old); UK university vs. overseas educated student.

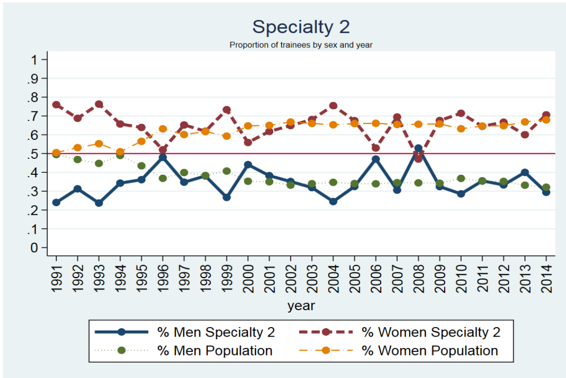
[d] Z-scores in parentheses: $***p < 0.01$; $**p < 0.05$ and $*p < 0.1$;

6.2 Appendix to Chapter 4

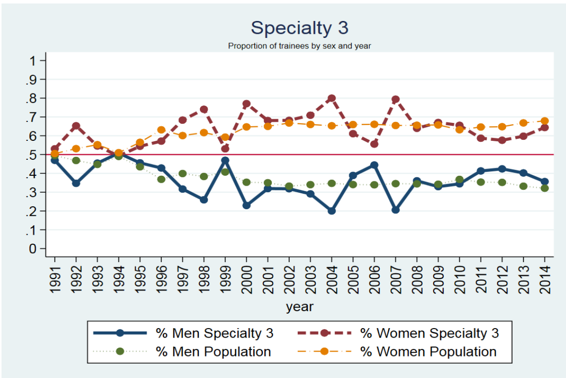
Figure A2.1: Proportion of male and female doctors by specialty



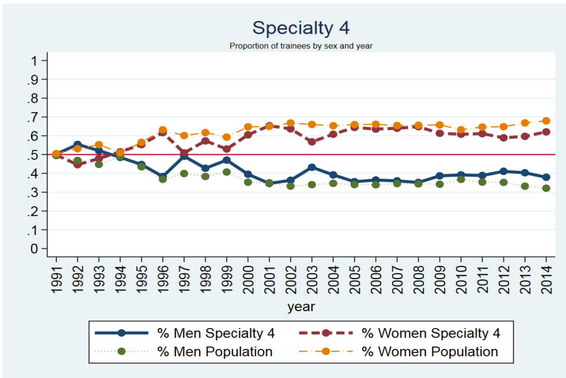
(a) Specialty 1: Allergy



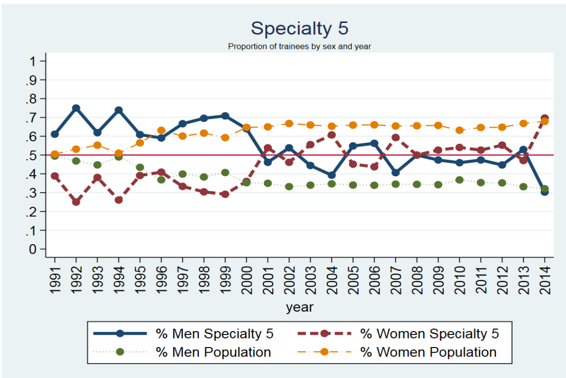
(b) Specialty 2: Clinical Analysis



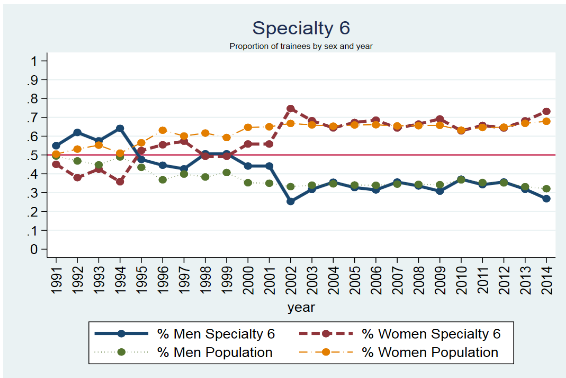
(c) Specialty 3: Anatomical Pathology



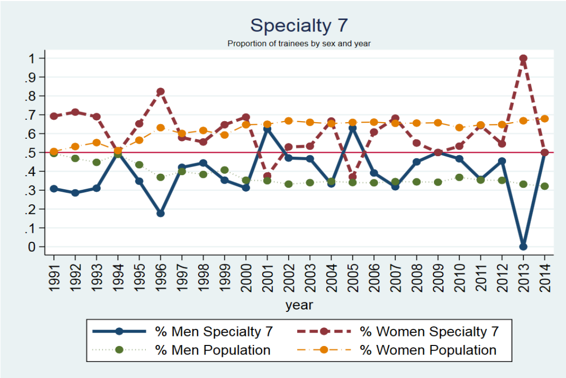
(d) Specialty 4: Anaesthetics



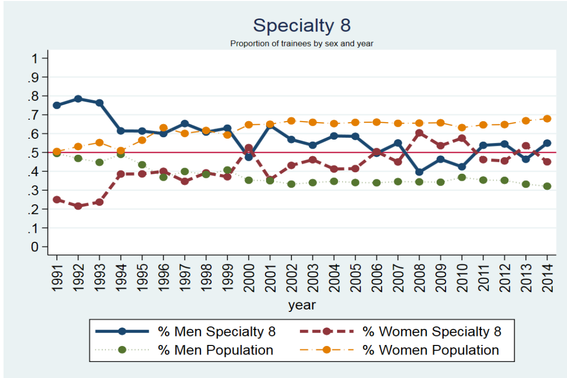
(e) Specialty 5:Vascular Surgery



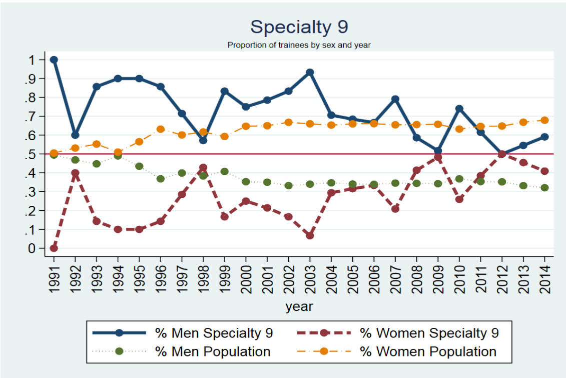
(f) Specialty 6:Gastroenterology



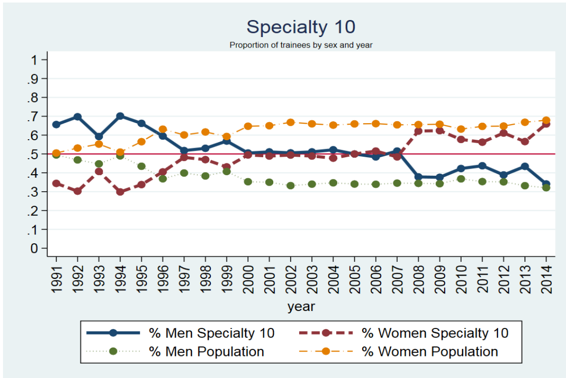
(g) Specialty 7:Clinical Biochemistry



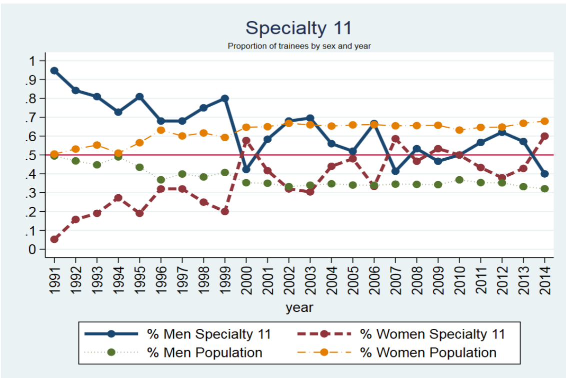
(h) Specialty 8: Cardiology



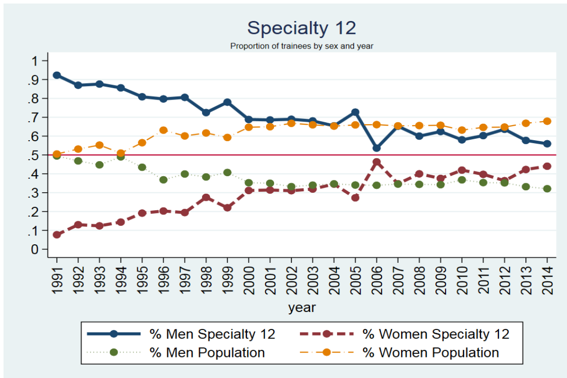
(i) Specialty 9: Cardiovascular Surgery



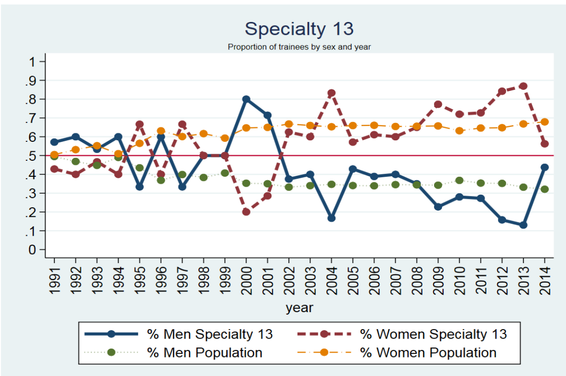
(j) Specialty 10: General Surgery



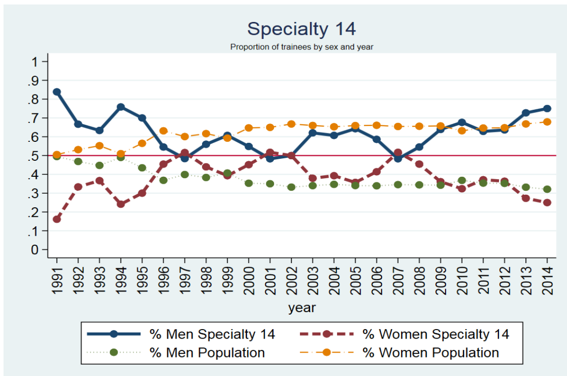
(k) Specialty 11: Oral Surgery



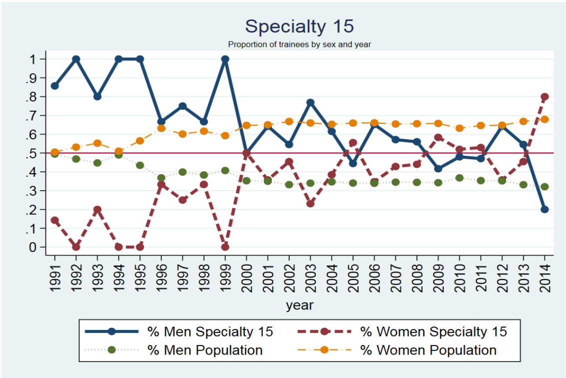
(l) Specialty 12: Orthopaedic Surgery



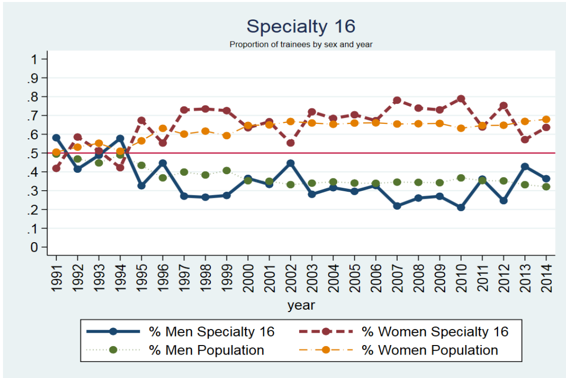
(m) Specialty 13: Paediatric Surgery



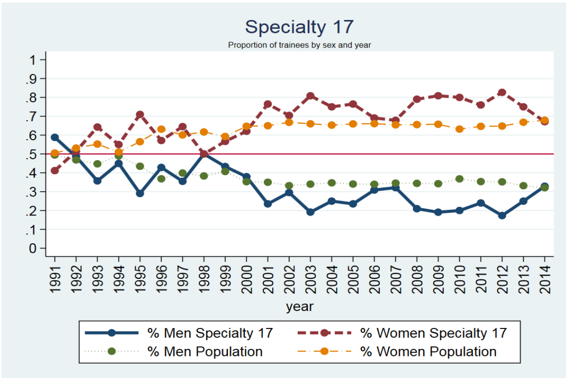
(n) Specialty 14: Plastic Surgery



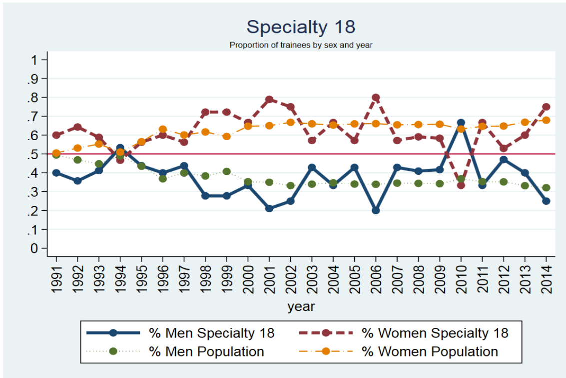
(o) Specialty 15: Thoracic Surgery



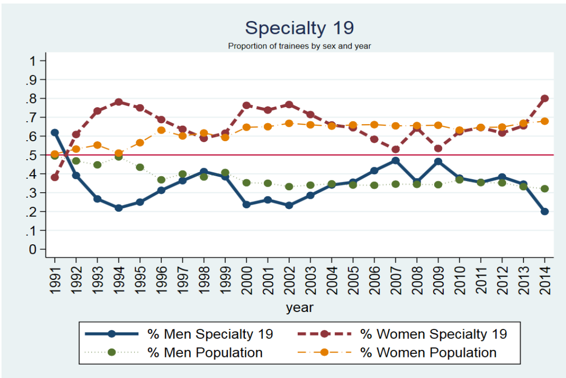
(p) Specialty 16: Dermatologic Surgery



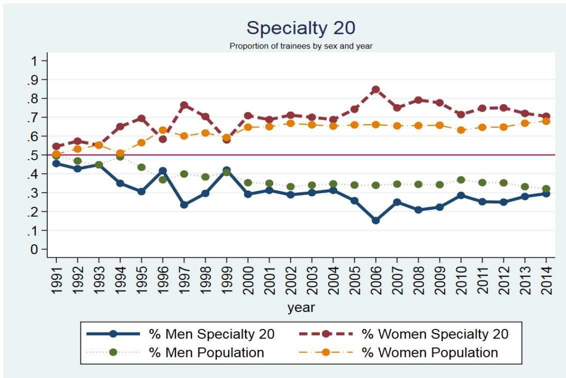
(q) Specialty 17: Endocrinology and Diabetes



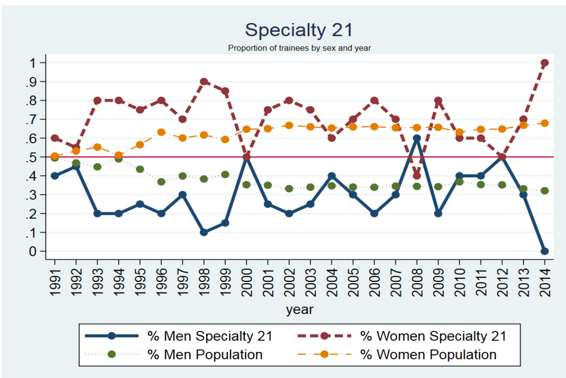
(r) Specialty 18: Pharmaceutical Medicine



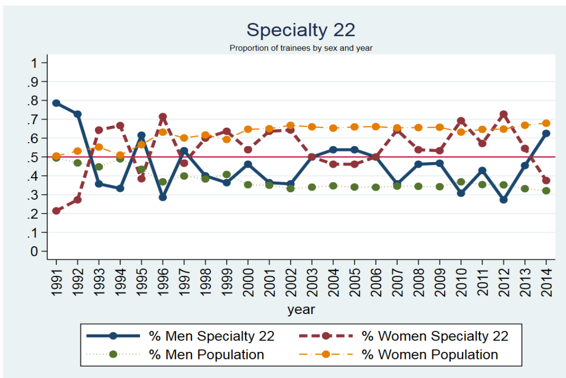
(s) Specialty 19: Geriatric Medicine



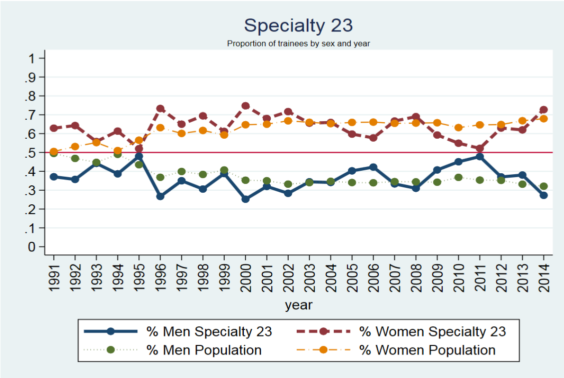
(t) Specialty 20: Haematology



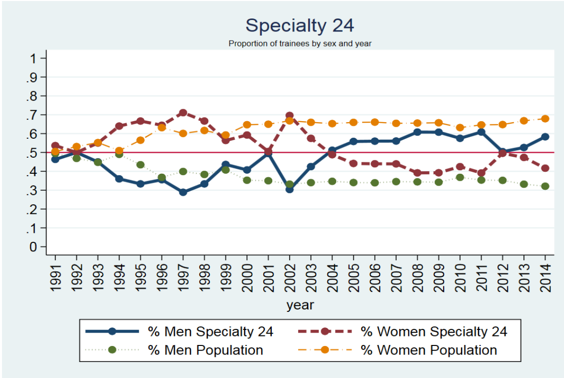
(u) Specialty 21: Medical Hydrology



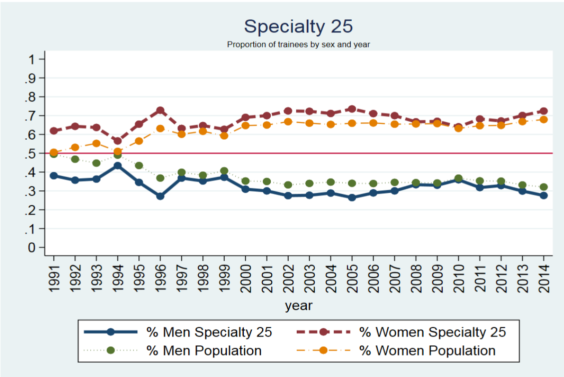
(v) Specialty 22: Immunology



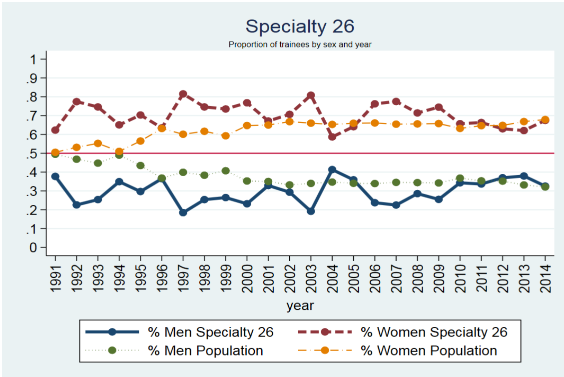
(w) Specialty 23: Occupational Medicine



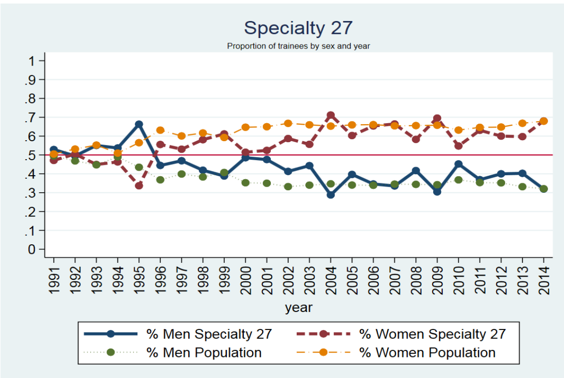
(x) Specialty 24: Sport and Exercise Medicine



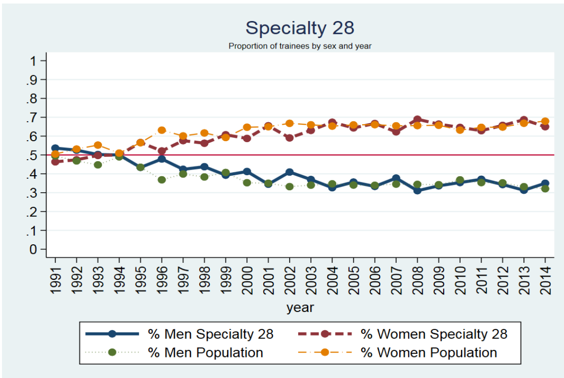
(y) Specialty 25: General Practice



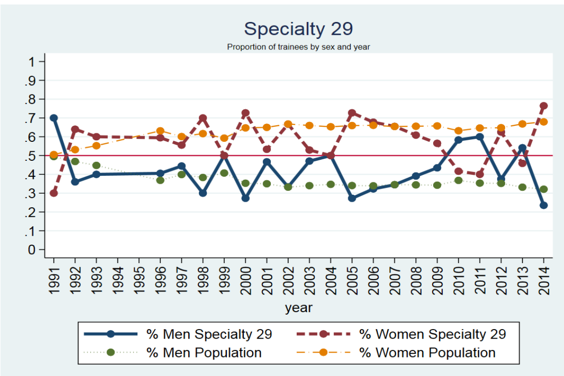
(z) Specialty 26: Rehabilitation Medicine



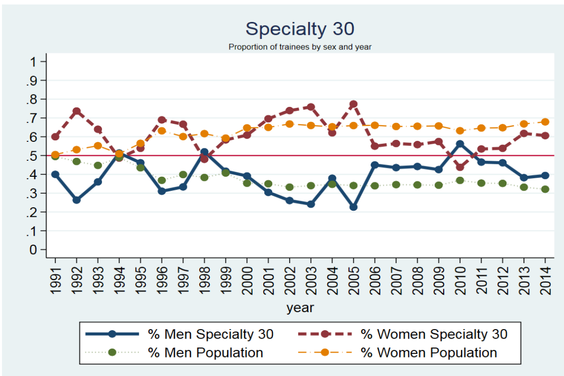
(aa) Specialty 27: Intensive Care Medicine



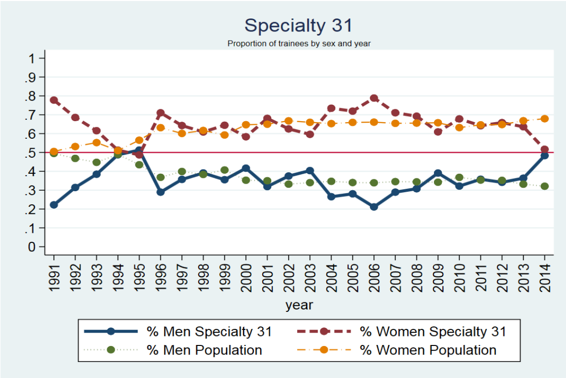
(ab) Specialty 28: General Internal Medicine



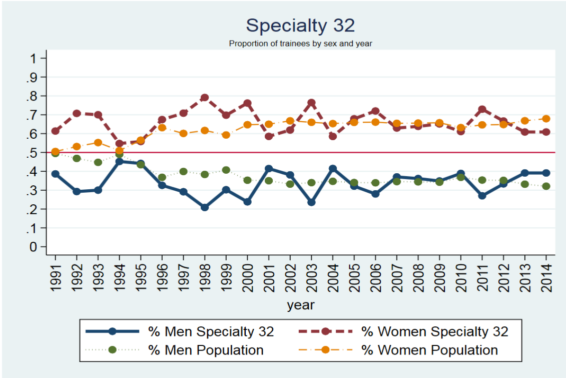
(ac) Specialty 29: Legal Forensic Medicine



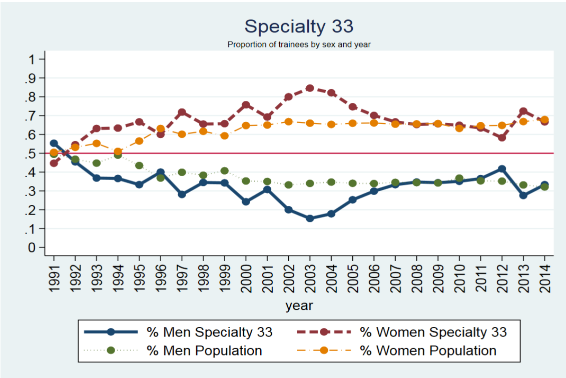
(ad) Specialty 30: Nuclear Medicine



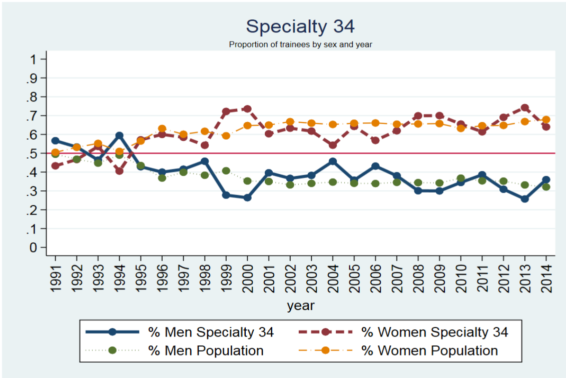
(ae) Specialty 31: Public Health



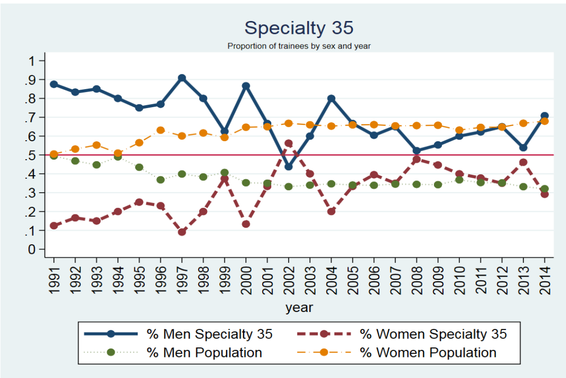
(af) Specialty 32: Microbiology



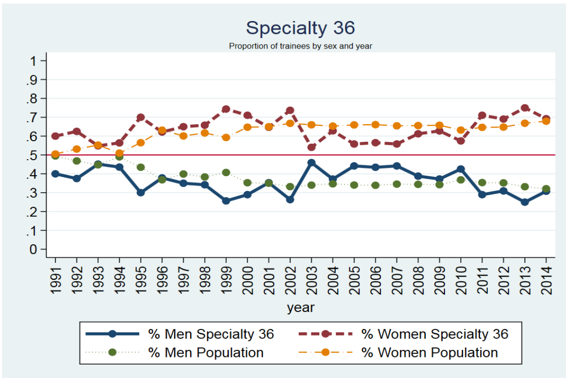
(ag) Specialty 33: Renal Medicine



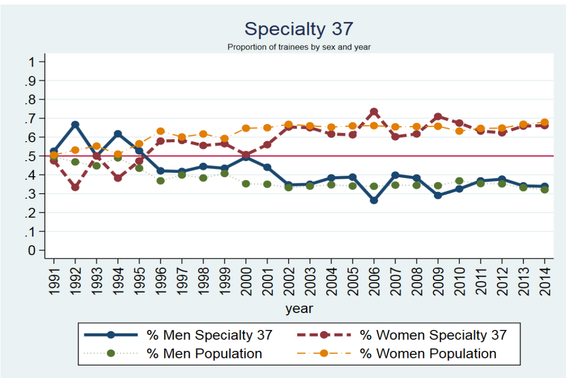
(ah) Specialty 34: Respiratory Medicine



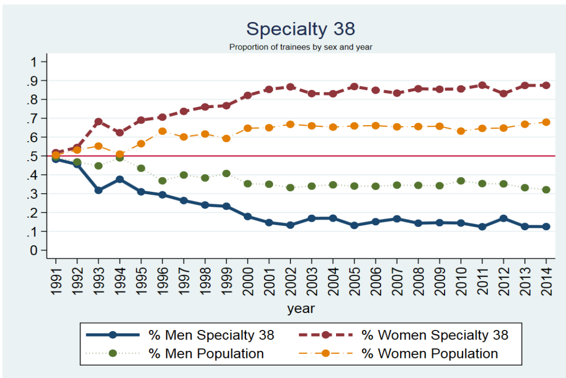
(ai) Specialty 35: Neurosurgery



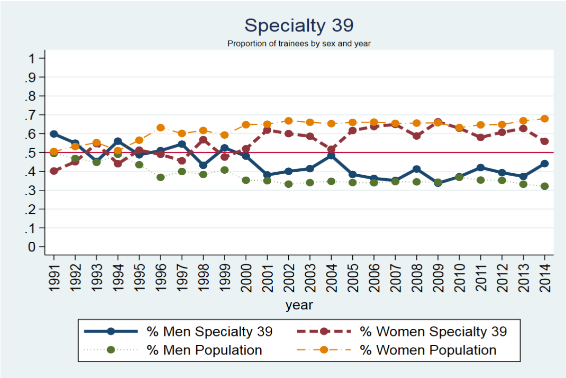
(aj) Specialty 36: Clinical Neurophysiology



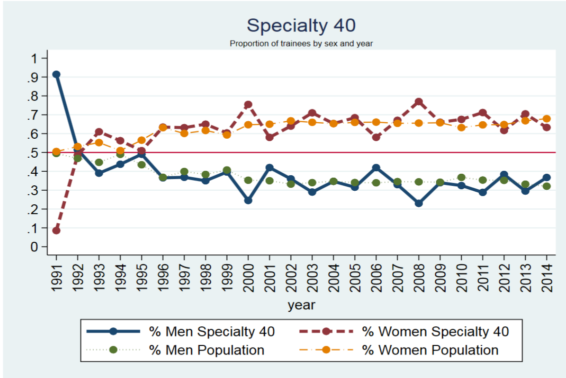
(ak) Specialty 37: Neurology



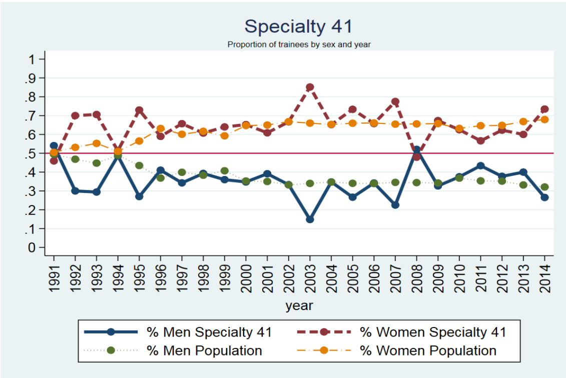
(al) Specialty 38: Obstetrics and Gynaecology



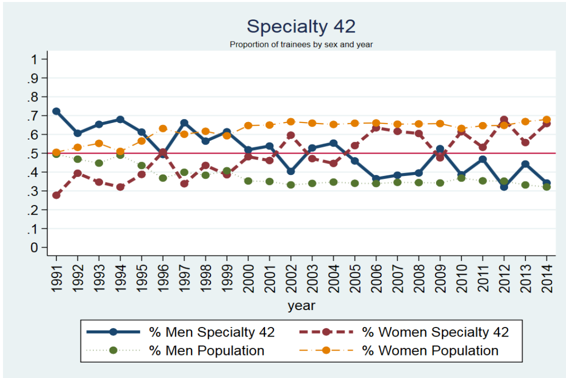
(am) Specialty 39: Ophthalmology



(an) Specialty 40: Medical Oncology



(ao) Specialty 41: Clinical Oncology



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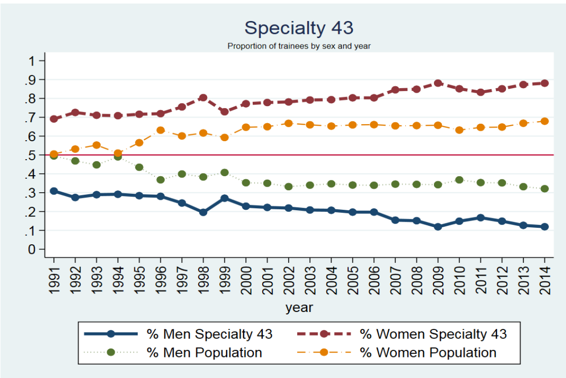

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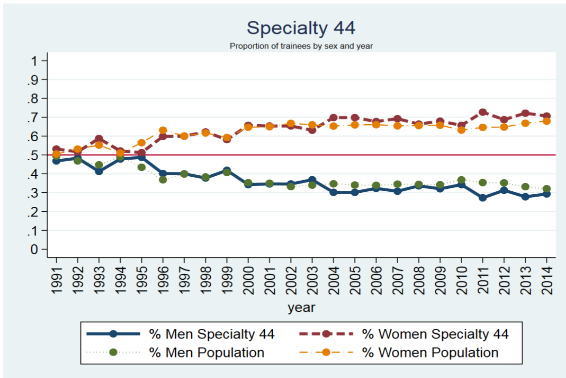

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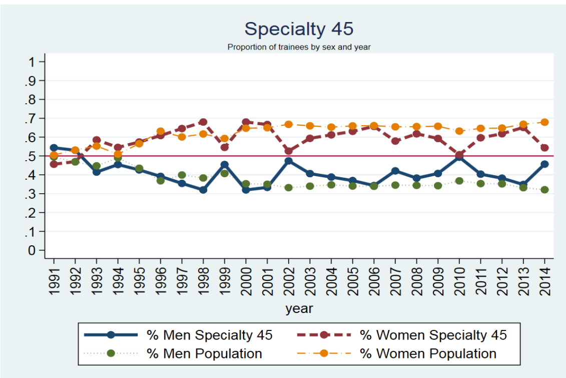

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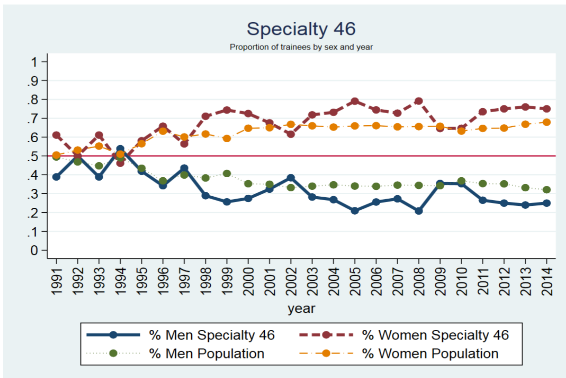
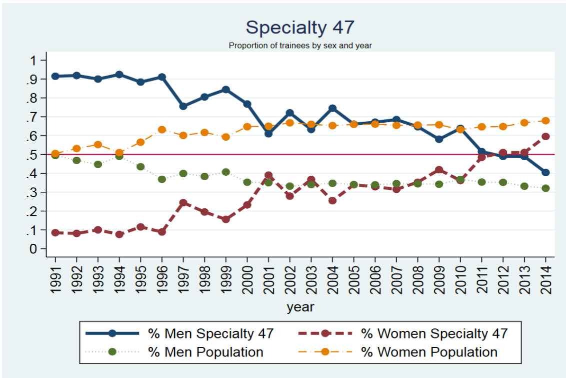


(at) Specialty 46: Rheumatology



(au) Specialty 47: Genito-Urinary Medicine

Abbreviations

AME	Average Marginal Effect
BME	Black and Minority Ethnic
FP	Foundation Programme
GMC	General Medical Council
GP	General Practitioner
GPA	Grade Point Average
LETB	Local Education and Training Board
MCAT	Medical College Admission Test
MIR	'Médico Interno Residente' (resident medical intern)
NHS	National Health System
NTS	National Training Survey
OB	Oaxaca-Blinder
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
POLAR3	Participation Of Local Areas
UK	United Kingdom
UKCAT	United Kingdom Clinical Aptitude Test
UKMED	United Kingdom Medical Education Data Set
US	United States

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