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

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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 paper analyses the functioning of the specialty allocation process in the UK and establishes the channels by which doctors' characteristics influence their specialty choices and selectors' valuations. For that purpose, we develop a conceptual framework that acknowledges the two-sided nature of the specialty allocation process: the application and selection stages. The framework also serves as the basis of the empirical analysis we perform. 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.

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 ethnic minority and male doctors experience differential attainment in the selection process for specialty training. The findings from this paper provide evidence of the occupational segregation of the new cohorts of doctors in training in UK and can be taken as a road map for policy makers to address the current policy concerns.

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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 et al., 2017) and foster policies targeted at improving the health outcomes of deprived populations and ethnic minorities (Cohen et al., 2002). However, there is 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 (Rodriguez Santana and Chalkley, 2017).

The research reported in this paper 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.

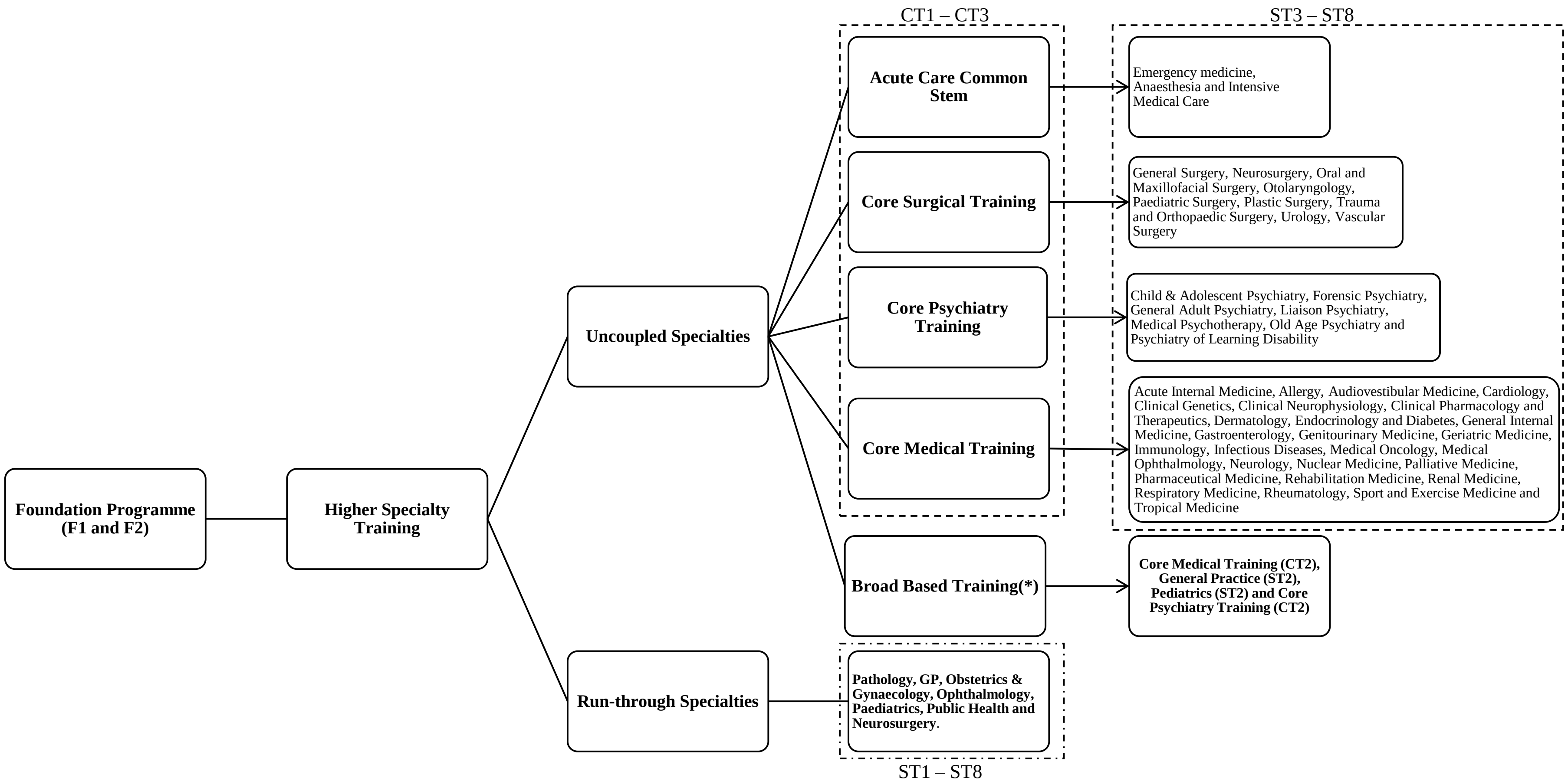
Second, we focus on the selection that takes place after doctors have made their specialty application choices. The interview is a crucial element of this selection stage. We analyse the role of demographic and socioeconomic characteristics in determining interview scores, controlling for previous educational 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.

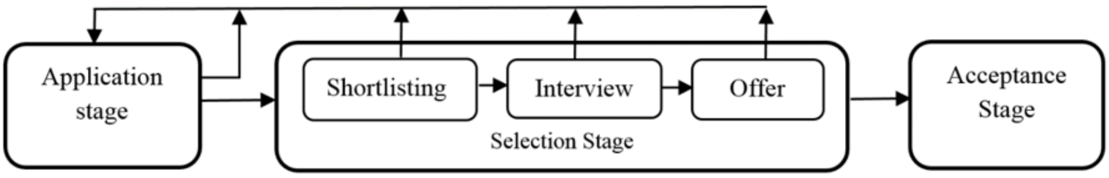
The reminder of this paper is organised as follows: in Section 2 we describe in detail the functioning of the specialty allocation process in the UK. Section 3 sets out the conceptual framework. Sections 4 and 5 set out the background, econometric model and results from the application and selection stages, respectively. Section 6 concludes the paper. Tables can be found in Section 7.

Figure 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 2: Stages in the specialty allocation process



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 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, 2017).

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[1] (LETB) on behalf of all LETBs. Figure 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 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

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

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[2] at any point and candidates who have accepted an offer can still apply to posts in subsequent recruitment rounds.

3 Conceptual framework

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 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

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

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.

3.2 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[3] SC_{ji} that is a function of student qualifications, experience and other elements. Those candidates whose SC_{ji} is above a certain 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]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.

4 Application stage

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, 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.

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.

4.2.1 Independent variables

Table 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[4] in the period 2013-2015 and zero otherwise.

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 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 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 also set out in Table 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

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

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 (2013), 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 paper. 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.

4.3 Econometric model and empirical implementation

Following the conceptual framework described in Section 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}.[5] The weighted net benefit is represented by A_{ji} that we define as a latent continuous variable that satisfies equation (1).

$$A_{ji} = Z_i^{'}\beta_j + \mu_{ji} \tag{1}$$

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 (2) shows this relationship.

$$y_{ji} = \begin{cases} 1 \; if & A_{ji} \geq 0 \\ 0 \; if & A_{ji} < 0 \end{cases} \tag{2}$$

[5] 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.

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:

$$P(y_{ji} = 1) = P(Z_i^{'}\beta_j + \mu_{ji} \geq 0) = P(-\mu_{ji} \leq Z_i^{'}\beta_j) = \Phi(Z_i^{'}\beta_j) \tag{3}$$

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 (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.

$$\frac{\partial P\left[y_{ji}|Z_i\right]}{\partial Z_{k_i}} = \frac{\partial \Phi(Z_i^{\prime}\beta)}{\partial Z_{k_i}} = \phi_i(Z_i^{'}\beta) * \beta_k \tag{4}$$

Empirical implementation

We analyse six different outcome variables, y_j, that result from grouping the specialties according to the domains described in Section 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), 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 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, 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.

4.4 Results: application stage

4.4.1 Descriptive statistics

Table 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[6] studies as different programmes have different lengths or can be done on a part-time basis.[7] In addition, medical students who have taken the option of intercalating[8] 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% 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%. We conjecture that a large proportion of the responses associated with the category unknown school must correspond to doctors who attended an independent school.[9] 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.*

[6] 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.

[7] 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.

[8] 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.

[9] The percentage of doctors attending independent schools is considerably smaller than the reported in Rodriguez Santana and Chalkley (2017) for the National Training Survey 2013 cohort.

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: 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 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 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 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 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 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 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.

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.[10] On 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 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.

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.

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

[10] According to Rimmer (2017) the gender pay gap has grown over the past decade. In 2006, female doctors working full time earned 24% less than their male colleagues whilst female doctors in 2016 earn 34% less.

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 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.

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 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.

5 Selection stage

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[11] 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[12] 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

[11] 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.

[12] The plan is known as Modernising Medical Careers (MMC).

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 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.

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 4.2 for a full description of the data. Similarly, Table 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 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 (5) gives the first transformation we apply:

$$IS_{ji}^{T1} = \frac{IS_{ji} - IS_j^{Min}}{IS_j^{Max} - IS_j^{Min}} \in [0, 1] \tag{5}$$

The transformed interview score IS_{ji}^{T1} ranges from 0 to 1, a feature that facilitates its interpretation. In equation (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 (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.[13]

[13]

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

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

$$IS_{ji}^{T2} = \frac{IS_{ji} - \mu_j^{IS}}{\sigma_j^{IS}} \sim \mathcal{N}(0,1) \quad (6)$$

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 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 (6).

We introduce *Specialty* dummy variables, one for each of the specialties on Table 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, effort 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.

5.3 Econometric model and empirical implementation

Following the conceptual framework described in Section 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.[14] Moreover, OLS estimates have a straightforward interpretation as the marginal effect of the covariate in the outcome variable. The relationship between interview score and the rest of covariates is represented by (7)

[14] 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.

$$IS_i^{TN} = \beta_0^N + DE_i^{'}\beta_1^N + SE_i^{'}\beta_2^N + AC_i^{'}\beta_3^N + OS_i^{'}\beta_4^N + \mu_i^N, \quad N = 1, 2 \tag{7}$$

Explanatory variables are classified into demographic ($DE^{'}$), socioeconomic ($SE^{'}$) and academic ($AC^{'}$) as Table 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), 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 12 sets out the covariates included in each specification.

Oaxaca-Blinder decomposition

As described in Section 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 (8) is a simplified version of (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 (9) where $E(\beta_g) = \beta_g$ and $E(\mu_g) = 0$.

$$Y_g = X_g \beta_g + \mu_g \tag{8}$$

$$D = E(Y_a) - E(Y_b) = E(X_a)^{'}\beta_a - E(X_b)^{'}\beta_b \tag{9}$$

To identify the contribution of group differences in explanatory covariates to the overall observed differences in interview score expression (9) can be rearranged as follows (Jann, 2008):

$$D = \underbrace{\{E(X_a) - E(X_b)\}^{'} \beta^*}_{E} + \underbrace{\{E(X_a)^{'}(\beta_a - \beta^*) - E(X_b)^{'}(\beta_b - \beta^*)\}}_{U} \tag{10}$$

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 (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 (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 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.

5.4 Results: Selection stage

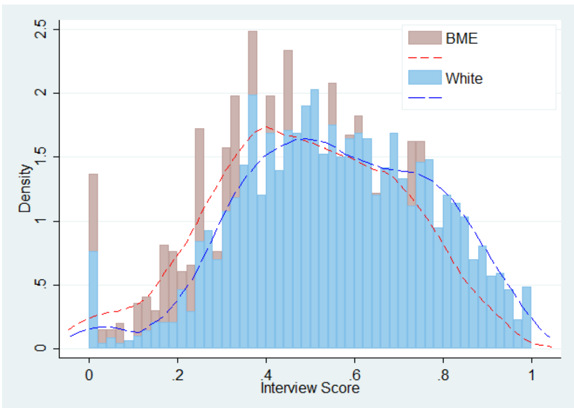
5.4.1 Descriptive statistics

Table 13 show the descriptive statistics for the sample of 3,055 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=3,550). The descriptive statistics do not display large differences in the explanatory variables between the two groups.

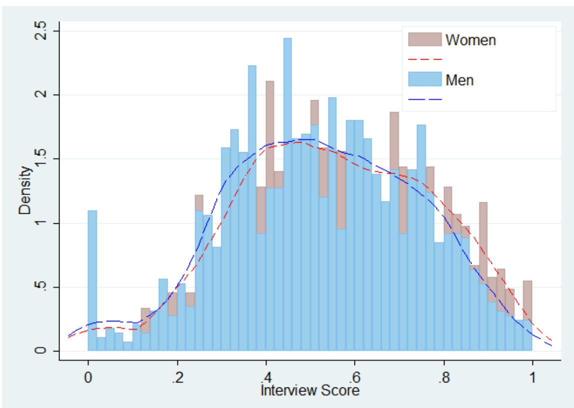
Table 14 shows the breakdown of descriptive statistics by gender and ethnicity. The comparison of the mean values of IS^{T1} highlights disparities between demographic groups. White doctors have a mean interview score of 0.56 whilst the mean is 0.49 for BME doctors. In the case of gender there are also differences, but of a smaller magnitude. The mean IS^{T1} for women is 0.55 and 0.52 for men. Figure 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 4: Kernel distributions of transformed interview score (IS^{T1}) by ethnicity and gender

(a) Ethnicity



(b) Gender



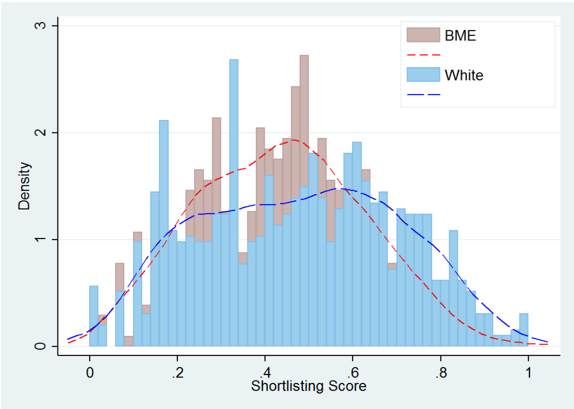
For shortlisting score (SC^{T1}) we observe a clear difference between white and BME doctors in the same direction as for IS^{T1} , however of a smaller magnitude, the associated means are 0.48 versus 0.44. No differences are observed for gender. Figure 5 shows that BME doctors are under-represented 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.

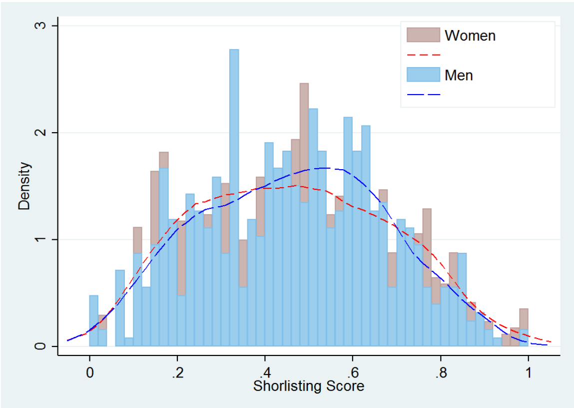
BME doctors are less likely to hold another degree at the start of medical school than white doctors, 24.7% versus 38.9% and they are also less likely to have attended a *Top 5 Uni*, 11.1% versus 12.9%. The results for UKCAT test scores are fairly similar across groups: BME doctors and women have the 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.

Figure 5: Kernel distributions of transformed shortlisting score (SC^{T1}) by ethnicity and gender

(a) Ethnicity



(b) Gender



5.4.2 Regression estimates

OLS

Table 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 13) 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 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 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.*

5.5 Robustness checks

Tables 18 and 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 20 shows the results. No statistically significant differences in means were found between the groups.

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,[15] 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. Interviewers may use observable characteristics from doctors like gender and ethnicity as proxy for unobservable, but outcome relevant characteristics.

Our sample descriptive statistics (Table 14) show that on average BME doctors have a lower shortlisting score than white doctors. Following Phelps (1972), in a situation 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 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 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 discrim-

[15]Equality Act 2010.

ination 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.

6 Conclusion

In this paper 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. 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.

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7 Tables

Table 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 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 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 2)
PrimaryC	Categorical	Equals 1 if the doctor applies to a primary care specialty and 0 otherwise	Application Stage	See Table 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 2 for the list of specialties classified as *Surgical*
Interview Score	Numerical	Interview score	Selection Stage	See Table 11
Shorlisting Score	Numerical	Shortlisting score	Selection Stage	

Table 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)						440	320
Broad Based Training (BBT)						230	110
Cardio-thoracic surgery (CTS)	x	x			x	35	10
Clinical radiology (CR)	x					290	145
Community Sexual and Reproductive Health (CSRH)	x			x		25	5
Core Anaesthetics Training (CAT)						920	610
Core Medical Training (CMT)						2280	1665
Core Psychiatry Training (CPT)			x			405	315
Core Surgical Training (CST)		x			x	1055	690
General Practice (GP)	x			x		3305	2465
Histopathology (HP)	x					60	45
Neurosurgery (NS)	x	x			x	80	30
Obstetrics and Gynaecology (O&G)	x			x	x	370	220
Ophthalmology (OPH)	x	x			x	190	65
Paediatrics (PAE)	x		x	x		630	480
Public Health Medicine (PHM)	x		x			70	20

Table 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 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	5,390	0.420	0.49	0	1	13,745	0.429	0.49	0	1
Gender: Women	7,630	0.581	0.49	0	1	5,390	0.580	0.49	0	1	13,745	0.571	0.49	0	1
Age Process	7,630	27.69	3.41	24	54	5,390	27.61	3.32	24	54	7,630	27.69	3.41	24	54
Age PMQ	7,630	25.60	3.39	22	52	5,390	25.51	3.30	22	52	13,745	25.32	2.97	22	52
Time Elapsed	7,630	2.089	0.29	2	4	5,390	2.095	0.30	2	4	7,630	2.089	0.29	2	4
Ethnicity: White	7,590	0.678	0.47	0	1	5,365	0.701	0.46	0	1	13,685	0.694	0.46	0	1
Ethnicity: BME	7,590	0.322	0.47	0	1	5,365	0.299	0.46	0	1	13,685	0.306	0.46	0	1
POLAR3: Low participation Neighbourhood	7,590	0.041	0.20	0	1	5,360	0.042	0.20	0	1	13,660	0.038	0.19	0	1
POLAR3: Non-UK Neighbourhood	7,590	0.098	0.30	0	1	5,360	0.077	0.27	0	1	13,660	0.086	0.28	0	1
POLAR3: Other Neighbourhood	7,590	0.861	0.35	0	1	5,360	0.881	0.32	0	1	13,660	0.876	0.33	0	1
School: State	7,630	0.639	0.48	0	1	5,390	0.648	0.48	0	1	13,745	0.632	0.48	0	1
School: Private	7,630	0.213	0.41	0	1	5,390	0.223	0.42	0	1	13,745	0.244	0.43	0	1
School:Unknown	7,630	0.148	0.36	0	1	5,390	0.129	0.34	0	1	13,745	0.124	0.33	0	1
Parent Doctor	7,630	0.113	0.32	0	1	5,390	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	5,390	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	5,390	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	5,390	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	5,390	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	5,390	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	5,390	0.329	0.47	0	1	13,745	0.493	0.50	0	1
Graduate: Yes	7,630	0.266	0.44	0	1	5,390	0.259	0.44	0	1	13,745	0.183	0.39	0	1
Graduate: No	7,630	0.734	0.44	0	1	5,390	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	4,610	25.13	2.23	16.3	33.4	12,095	25.24	2.20	16.3	33.4
Top 5 Uni	7,630	0.123	0.33	0	1	5,390	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	5,390	0.503	0.50	0	1					
TopInc	7,630	0.109	0.31	0	1	5,390	0.134	0.34	0	1					
BottomInc	7,630	0.143	0.35	0	1	5,390	0.101	0.30	0	1					
PrimaryC	7,630	0.530	0.50	0	1	5,390	0.459	0.50	0	1					
Surgical	7,630	0.204	0.40	0	1	5,390	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	5,390	0.332	0.47	0	1					
Women*TopInc	7,630	0.039	0.19	0	1	5,390	0.048	0.21	0	1					
Women*BottomInc	7,630	0.096	0.30	0	1	5,390	0.069	0.25	0	1					
Women*PrimaryC	7,630	0.352	0.48	0	1	5,390	0.311	0.46	0	1					
Women*Surgical	7,630	0.099	0.30	0	1	5,390	0.081	0.27	0	1					
BME*AppliMore	7,590	0.111	0.31	0	1	-	-	-	-						
BME*RunThrou	7,590	0.202	0.40	0	1	5,365	0.154	0.36	0	1					
BME*TopInc	7,590	0.043	0.20	0	1	5,365	0.051	0.22	0	1					
BME*BottomInc	7,590	0.041	0.20	0	1	5,365	0.022	0.15	0	1					
BME*PrimaryC	7,590	0.174	0.38	0	1	5,365	0.137	0.34	0	1					
BME*Surgical	7,590	0.085	0.28	0	1	5,365	0.062	0.24	0	1					

Table 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)	
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

Continued on next page

Table 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
			(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	7,555		7,555		6,440		5,335		5,335		4,575	
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 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)	
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

Continued on next page

Table 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
			(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	7,555		7,555		6,440		5,335		5,335		4,575	
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 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)	
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

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Table 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
			(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	7,555		7,555		6,440		5,305		5,305		4,575	
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 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)	
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

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Table 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
			(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	7,555		7,555		6,440		5,335		5,335		4,575	
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 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)	
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

Continued on next page

Table 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
			(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	7,555		7,555		6,440		5,335		5,335		4,575	
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 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	7,555		7,555		7,555		7,555		7,555		7,555	
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 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	380
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	100
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	10
Clinical radiology	92.95	33.19	0	47	147	260	0.549	0.171	0	1	0.243	0.524	-1.363	1.628	240
Community Sexual and Reproductive Health						5**									5
Core Anaesthetics Training	134.31	22.14	79	79	207	340	0.432	0.173	0	1	0.077	0.86	-2.246	3.838	340
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	900
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	165
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	980
General practice	50.37	39.74	0	1	69	395	0.639	0.37	0	1	0.262	0.809	-1.651	1.701	320
Histopathology	386.59	169.8	0	231	546	55	0.698	0.202	0	1	0.363	0.404	-1.581	0.903	50
Neurosurgery	135.27	29.7	0	0	172.3	40	0.785	0.172	0	1	0.263	0.505	-1.184	1.2467	40
Obstetrics and gynaecology	84.48	18.74	0	59	110	160	0.552	0.22	0	1	0.159	0.575	-1.359	1.362	160
Ophthalmology	106.91	20.79	0	47.3	159	145	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	260
Public health medicine	50.22	16.14	0	40.2	64	35	0.613	0.218	0	1	0.306	0.296	-0.371	0.853	35

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

**Average suppressed where population is 7 or fewer individuals

Table 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 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	3,055	0.463	0.499	0	1	3,550	0.470	0.499
Gender: Woman	3,055	0.537	0.499	0	1	3,550	0.530	0.499
Ethnicity: White	3,055	0.677	0.468	0	1	3,550	0.667	0.471
Ethnicity: BME	3,055	0.323	0.468	0	1	3,550	0.333	0.471
Age Process	3,055	27.952	3.470	24	54	3,550	28.043	3.543
Time Elapsed	3,055	2.064	0.249	2	4	3,550	2.062	0.246
Parent doctor	3,055	0.105	0.307	0	1	3,550	0.101	0.301
School: School	3,055	0.629	0.483	0	1	3,550	0.622	0.485
School: Independent	3,055	0.193	0.395	0	1	3,550	0.186	0.389
School: Unknown	3,055	0.178	0.382	0	1	3,550	0.192	0.394
POLAR3: Low participation Neighbourhood	3,035	0.043	0.204	0	1	3,530	0.043	0.204
POLAR3: Non-UK Neighbourhood	3,035	0.121	0.326	0	1	3,530	0.132	0.339
POLAR3: Other Neighbourhood	3,035	0.836	0.371	0	1	3,530	0.825	0.380
Graduated on entry	3,055	0.343	0.475	0	1	3,550	0.353	0.478
Top 5 University	3,055	0.123	0.329	1	2	3,555	0.127	0.333
UKCAT Score	2,445	25.140	2.253	16.3	32.5	2,820	25.147	2.266
Year Medical School: 2007	3,055	0.730	0.444	0	1	3,550	0.737	0.440
Year Medical School: 2008	3,055	0.270	0.444	0	1	3,550	0.263	0.440
Interview Score transformed (1)	3,055	0.538	0.217	0	1	3,550	0.532	0.211
Interview Score transformed (2)	3,055	0.198	0.707	-2.6	3.8	3,550	0.180	0.689
Shortlisting Score transformed (1)	1,485	0.463	0.216	0.0	1	1,850	0.461	0.213
Shortlisting Score transformed (2)	1,485	-0.018	0.954	-3.0	4.1	1,850	-0.013	0.948
Nr Applications	3,055	1.379	0.622	1	5	3,550	1.531	0.757
AppliMore	3,055	0.314	0.464	0	1	3,555	0.410	0.757
Year Process: 2012	3,055	0.013	0.115	0	1	3,550	0.015	0.123
Year Process: 2013	3,055	0.140	0.347	0	1	3,550	0.148	0.355
Year Process: 2014	3,055	0.487	0.500	0	1	3,550	0.493	0.500
Year Process: 2015	3,055	0.360	0.480	0	1	3,550	0.344	0.475

Table 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	2,065	0.443	0.497	990	0.506	0.500	-	-	-	-	-	-
Gender: Woman	2,065	0.557	0.497	990	0.494	0.500	-	-	-	-	-	-
Ethnicity: White	-	-	-	-	-	-	1,415	0.647	0.478	1,640	0.702	0.457
Ethnicity: BME	-	-	-	-	-	-	1,415	0.353	0.478	1,640	0.298	0.457
Age Process	2,065	28.166	3.651	990	27.505	3.010	1,415	28.124	3.719	1,640	27.803	3.234
Time Elapsed	2,065	2.069	0.259	990	2.055	0.228	1,415	2.059	0.242	1,640	2.068	0.255
Parent doctor	2,065	0.083	0.276	990	0.153	0.360	1,415	0.120	0.325	1,640	0.093	0.290
School: State	2,065	0.684	0.465	990	0.515	0.500	1,415	0.615	0.487	1,640	0.642	0.480
School: Independent	2,065	0.187	0.390	990	0.205	0.404	1,415	0.213	0.409	1,640	0.176	0.381
School:Unknown	2,065	0.129	0.335	990	0.281	0.450	1,415	0.172	0.378	1,640	0.183	0.386
POLAR3: Low participation Neighbourhood	2,050	0.048	0.214	985	0.034	0.180	1,405	0.047	0.212	1,630	0.040	0.197
POLAR3: Non-UK Neighbourhood	2,050	0.051	0.220	985	0.266	0.442	1,405	0.112	0.315	1,630	0.129	0.335
POLAR3: Other Neighbourhood	2,050	0.901	0.299	985	0.700	0.458	1,405	0.841	0.366	1,630	0.831	0.375
Graduated on entry	2,065	0.389	0.488	990	0.247	0.432	1,415	0.329	0.470	1,640	0.355	0.479
UKCAT Score	1,650	25.347	2.189	800	24.713	2.325	1,130	25.343	2.231	1,315	24.965	2.259
Top 5 University	2,070	0.129	0.336	990	0.111	0.315	1,415	0.131	0.337	1,640	0.117	0.322
Year Medical School: 2007	2,070	0.733	0.443	990	0.724	0.447	1,415	0.726	0.446	1,640	0.734	0.442
Year Medical School: 2008	2,070	0.267	0.443	990	0.276	0.447	1,415	0.274	0.446	1,640	0.266	0.442
Interview Score transformed (1)	2,070	0.561	0.216	990	0.488	0.212	1,415	0.523	0.214	1,640	0.550	0.219
Interview Score transformed (2)	2,070	0.277	0.672	990	0.032	0.749	1,415	0.149	0.727	1,640	0.241	0.686
Shortlisting Score transformed (1)	970	0.478	0.227	515	0.435	0.191	630	0.463	0.209	855	0.463	0.221
Shortlisting Score transformed (2)	9,670	0.053	0.969	515	-0.153	0.909	630	-0.038	0.957	855	-0.004	0.952
Nr Applications	2,070	1.336	0.581	990	1.467	0.693	1,415	1.341	0.596	1,640	1.411	0.643
AppliMore	2,070	0.286	0.452	990	0.373	0.484	1,415	0.283	0.451	1,640	0.341	0.474
Year Process: 2012	2,070	0.007	0.085	990	0.026	0.160	1,415	0.013	0.112	1,640	0.014	0.118
Year Process: 2013	2,070	0.152	0.359	990	0.114	0.319	1,415	0.140	0.347	1,640	0.139	0.346
Year Process: 2014	2,065	0.515	0.500	990	0.430	0.495	1,415	0.428	0.495	1,640	0.538	0.499
Year Process: 2015	2,065	0.327	0.469	990	0.430	0.495	1,415	0.419	0.494	1,640	0.309	0.462

Table 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	1,480	1,150	3,035	3,035	1,480	1,150
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 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	1,480	1,150	3,035	3,035	1,480	1,150
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 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	1,480	1,150	3,035	3,035	1,480	1,150
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 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	900	800	140	690	690	685	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 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	800	800	140	690	690	685	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 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	1,480	1,150	3,035	3,035	1,480	1,150
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: $***p < 0.01, **p < 0.05, *p < 0.1$