

Gender Differences in Early Occupational Choices: Evidence from Medical Specialty Selection

Josep Amer-Mestre* and Agnès Charpin†

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Abstract

Empirical evidence shows that men and women hold different types of occupations. It is however difficult to disentangle the channels via which these differences come about because observed equilibrium outcomes arise from preferences of agents on both sides of the market, and search and matching frictions. This paper relies on a unique labour market setting allowing to isolate the supply side factors driving gender-based occupational segregation. We find that supply-side factors are important. Female and male medical students facing the same pool of available positions make drastically different occupational decisions, even at the top of the performance distribution. Women prefer occupations characterised by lower expected earnings and time requirements, less competition, and a higher social contribution. We also find evidence suggesting that when constrained in their choices, women have a stronger preference for the location in which they are going to live compared to their male counterparts.

Keywords: Occupational segregation, Gender, Labour market, Job attributes

JEL Classification: J22, J24, J31, J71

*Department of Economics, European University Institute, Italy, josep.amer@eui.eu.

†Department of Applied Economics, Université libre de Bruxelles, Belgium, agnes.charpin@ulb.be.

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1 Introduction

Over the past decades, women have made important progress on the labour markets of most developed countries, resulting into what [Goldin \(2014\)](#) refers to as one of the “grandest advances in society and the economy”: the converging roles of men and women. The gender gaps in labour force participation and earnings have been reduced, and women overtook men in their educational attainments. Despite these changes, gender-based occupational segregation keeps being a strong feature of the labour markets of most developed countries.

Traditionally, economists have focused on the role of human capital accumulation and discrimination as the drivers of gender-based occupational segregation and gender differences in labour market outcomes ([Altonji and Blank, 1999](#)). In the past decade, however, the literature has turned to new classes of explanations for these differences.¹ To this day, standard observational datasets often only offer the possibility to work with realised labour market outcomes, but rarely contain detailed information on the factors leading to the observed match between a job seeker and a job. They seldom contain information allowing to identify the set of jobs that a job seeker can apply to, define the likelihood that a job seeker gets a job, nor they allow to account for search and matching frictions. This myriad of confounding factors resulting into the equilibrium outcomes hinders the empirical disentanglement of the different channels that can explain gender-based occupational segregation.

In this paper, we analyse gender differences in early occupational choices in a context which allows to focus on the role of job seekers’ preferences for specific job characteristics, such as its expected earnings, amenities, and location. We use administrative and survey data drawn from a one-sided matching job market for highly skilled individuals which, by design, is exempt from demand-side preferences and search and matching frictions, and allows to observe individual occupational choice sets.

Specifically, we analyse the occupational choice of medical students in France, using data on the allocation mechanism of students to medical residency positions. This allocation procedure is an application of the Deferred Acceptance algorithm developed by [Gale and Shapley \(1962\)](#). Each year, all the medical students at the end of their sixth year of studies take a nationwide exam (henceforth the National Ranking Examinations² or NRE) and are ranked according to their sole performance. The available vacancies for each position—defined as a medical specialty and a geographical location pair—are then made public. At that stage, candidates submit an ordered list of their preferred positions on an online platform, which they can adjust as frequently as they want until their allocation turn. This period, which we refer to as the simulation phase, allows candidates to observe the position that they would get if the allocation process was to happen at a given point in time. Finally, on allocation days, vacancies are filled on a first

¹See [Bertrand \(2011\)](#), [Cortes and Pan \(2017\)](#), [Azmat and Petrongolo \(2014\)](#) and [Blau and Kahn \(2016\)](#) for detailed accounts of the directions that the literature has taken over the past years.

²*Épreuves classantes nationales.*

ranked, first served basis, until all candidates have been allocated to a position.

This setting has five unique features. First, given that employers' preferences play no role in the matching process, there is no room for direct discrimination from employers. Second, there is perfect information over the set of occupations that each candidate can pick from, and it is observable to us. This considerably minimises the potential role of gender differences in ability to search and apply for jobs in explaining gender differences in occupational choices. Third, the matching of applicants to vacancies occurs via a frictionless mechanism that leaves no room for bargaining. This is crucial, considering the increasing evidence from laboratory and non-experimental studies showing that women tend to avoid environments which require to negotiate or bargain (e.g. [Biasi and Sarsons, 2020](#)).

These first three features imply that, unlike in most labour market settings, we are able to shut down the demand side of the market and focus entirely on the supply side. In other words, on this market, the decision power is entirely concentrated on the job seeker's side. This has two main implications. It allows to compare the occupational choices of individuals facing the same pool of available positions. Furthermore, the allocation mechanism ensures job seekers' true preference elicitation, since their optimal strategy is always to select their most preferred position within the available ones.

Fourth, this setting allows to identify a group of individuals who, given their performance at the National Ranking Examinations, make their occupational choice when *all* positions still offer at least one vacancy. It implies that they are free to pick their preferred specialty in their preferred geographical location. Unlike the rest of the candidates, they do not face the occupation-location trade-off which, by design, emerges and intensifies as positions are filled. This last feature has one main implication: unlike in most settings in which the researcher only observes realised outcomes, we are able to identify the preferred occupational choice of a group of individuals. Thereafter, we refer to these individuals as *unconstrained*.

Fifth, the occupational choice that we focus on is decisive, given that it determines the field in which physicians will specialise and work for the rest of their career. Finally, job seekers on this market form a very homogeneous group of young and highly skilled individuals holding the same formal qualifications, which reduces the existence of potential factors confounding the occupational decision, like childbearing, even further.

Using individual-level data on this allocation mechanism, we first estimate gender differences in occupational choices separately for candidates who are constrained and unconstrained regarding the occupational choice set that they face. We find that conditional on facing the same choice set, men and women make drastically different occupational choices. Strikingly, we find that this is true at the top of the performance distribution, where all positions are still available and thus candidates do not face any external constraint on their choices. It implies that men and women facing the same choice sets *prefer* different occupations, and thus suggests that individual preferences play an important role in determining

occupational segregation.

Next, we identify pecuniary and non-pecuniary workplace attributes which attract men and women differently. We show that men and women self-select into occupations that are significantly different: conditional on facing the same occupational choice set, women are more likely than men to select into occupations which have lower expected earnings and time requirements, have less competitive environments, but a higher social component.

Finally, we leverage the benefits of the residency selection process and novel data on revealed and stated preferences for residency positions to investigate whether men and women differ in their preference for geographical mobility. The decision on where to live and work is a crucial one for young individuals entering the labour force; and one that medical students starting their specialisation need to make. We find evidence suggesting that women have a stronger preference for the location in which they work than their male counterparts, and that the positions they consider taking are more likely to be geographically closer to one another.

This paper contributes to the large literature on gender differences in labour market outcomes. The two factors which were originally put forward by the literature as the main drivers of gender-based occupational segregation and differences in labour market outcomes are discrimination (taste-based or statistical) and human capital accumulation (via education and work experience) (Altonji and Blank, 1999). The former channel has received recent support from a growing empirical literature documenting the existence of a gap in the probability that men and women are interviewed or hired for the same job (e.g. Goldin and Rouse, 2000; Riach and Rich, 2002; Rich, 2014; Neumark, 2018). Regarding the latter channel, recent work shows that even though women have now surpassed men in terms of educational attainments (Goldin, Katz and Kuziemko, 2006), there still exist marked gender differences in labour force participation and career development (Bertrand, Goldin and Katz, 2010).

The particular design of the job market studied in this paper ensures that the gender differences that we document cannot be explained by these factors. In our setting, employers play no role in the hiring process: they do not screen, evaluate, nor decide whether to hire candidates. Moreover, job seekers in this market are homogeneous in terms of age, educational attainment and work experience. To the best of our knowledge, no other paper exploits a job market in which employer discrimination is completely ruled out, allowing to focus entirely on the supply side of the market, and in which job seekers arguably form a very homogeneous group.

In the past decade, labour economists have started considering new classes of explanations for gender differences on the labour market.³ Among them are differences in personality traits (e.g. Dohmen et al., 2011; DeLeire and Levy, 2004; Flory, Leibbrandt and List, 2014; Buser, Niederle and Oosterbeek, 2014;

³See Bertrand (2011), Cortes and Pan (2017) and Azmat and Petrongolo (2014) for detailed accounts of the directions that the literature has taken over the past years.

Reuben, Sapienza and Zingales, 2015; Reuben, Wiswall and Zafar, 2017), differences in preferences for certain workplace amenities (e.g. Lordan and Pischke, 2016; Cortes and Pan, 2017; Fluchtmann et al., 2020; Fortin, 2008; Wiswall and Zafar, 2017; Wasserman, 2019; Sasser, 2005; Le Barbanchon, Rathelot and Roulet, 2019; Fadlon, Lyngse and Nielsen, 2020), and social norms about what women can and should do (e.g. Akerlof and Kranton, 2000; Goldin, 2002; Charles, Guryan and Pan, 2018). While there exist plenty of studies using the laboratory to analyse these new classes of explanations,⁴ there is limited evidence of their relevance on actual labour market outcomes, because of the difficulty behind disentangling the many elements leading to gender differences in labour market outcomes.

Our paper contributes to this growing strand of the literature providing evidence of the role of work content and context in determining gender differences on the labour market by bringing the following major improvements. First, the absence of employer discrimination and the homogeneity of the population of job seekers under study improve on two of the closest papers to ours, Lordan and Pischke (2016) and Cortes and Pan (2017), in which job seekers' formal qualifications might differ, and demand side factors are present. Second, job markets in which one can observe the occupational choice set that job seekers face during their search, and thus compare the occupational decisions of men and women facing the same choice set, are very rare. To the best of our knowledge, no other paper uses such accurate data on occupational availability and can therefore control for potential gender differences in availability of positions, and in ability to search and apply for jobs.

Third, this job market leaves no room for bargaining over working conditions. This is crucial, as a growing body of empirical studies provides evidence suggesting that women are more reluctant than men to bargain (e.g. Babcock and Laschever, 2003; Dittrich, Knabe and Leipold, 2014; Exley, Niederle and Vesterlund, 2016; Biasi and Sarsons, 2020). Finally, our setting allows to identify a group of individuals who make their decision at a time when all the positions are still available, and who thus make a fully unconstrained occupational choice. To our knowledge, our paper is the first to focus on a setting in which observed and preferred occupational outcomes coincide.

The rest of the paper is organised as follows: section 2 presents the setting under study and our different data sources. Sections 3 and 4 present our empirical strategy and main results: they document the gender differences in occupational choices, and the gender differences in preferences for different job attributes, respectively. Sections 5 and 6 provide additional results on gender differences in preferences for mobility, and on the gendered effect of having a partner when making the occupational decision. Finally, section 7 concludes.

⁴To name a few, Croson and Gneezy (2009); Eckel and Grossman (2008) review the laboratory evidence on risk aversion and conclude that women are more risk averse than men. Niederle, Gneezy and Rustichini (2003); Niederle and Vesterlund (2007) focus on the gender differences in behaviours in competitive environments. They find evidence that women underperform relative to men in competitive environments, and that the gender composition of the environment matters.

2 Institutional Setting and Data

2.1 The Medical Curriculum in France

The French medical curriculum starts with a very selective first year, at the end of which all students must take a national exam that less than 20 percent of the competing students pass, on average.⁵ The next two years of the curriculum are devoted to developing a wide and general set of skills. The fourth, fifth and sixth years of medical studies are devoted to preparing the National Ranking Examinations (thereafter NRE), after which students obtain a master-level degree and are assigned to a residency program according to their performance at the NRE. The residency choice consists in selecting a medical specialty and a geographical location in which to specialise until the completion of one's training. After being assigned to a residency position, residents are no longer considered only as students, but also as members of the medical staff of the hospital in which they work.

Allocation of students into residency positions is done following a classical Deferred Acceptance algorithm (Gale and Shapley, 1962). The NRE is organised by the *Centre national de gestion* (hereafter CNG) an establishment under the supervision of the Ministry of Health and in charge of the recruitment and management of public hospital staff and of practitioners. The NRE is composed of two days of examinations, resulting in a unique national ranking of all the students in their sixth year of medical studies. After the examinations have taken place, the Ministry of Health releases that year's number of available vacancies for each specialty and geographical location pair.⁶ After the national ranking of candidates has been made public, a simulation period for the selection of residency positions starts. This period lasts around four weeks and aims at guiding candidates in their choice of specialty and location. During this period, candidates submit an ordered list of their preferred residency positions to an online platform, ranging from one to as many positions as there are. This list can be updated at any point in time during the simulation phase until the moment of their official allocation. The platform then combines the number of available vacancies and the candidates' lists of preferences to perform allocation simulations every five minutes. Therefore, each student can see at any point in time the position that they would get if the allocation process was to take place at that moment.⁷

Finally, on allocation days, candidates pick their final allocation according to their rank: the best ranked chooses first, then the second-best ranked chooses, and so on, until all the students are matched to a specialty, location pair. This process is performed using the same platform and the same list of

⁵This strict regulation of entries follows from the large increase in the number of medical students that occurred in the late sixties and early seventies. As the baby-boomers started graduating from higher education, it became clear that the excessive number of physicians was going to affect negatively their individual earnings, hence in 1971, the government imposed a *numerus clausus* on the number of medical students allowed to pursue their studies after this first year. It reached its lower level of 3,500 in 1993, and increased steadily since then.

⁶This usually occurs before the national ranking is made public.

⁷The simulation phase is split between an "unofficial" phase and an "official" phase. The unofficial phase occurs first, and is meant to help candidates decide whether they want to request an exemption to re-take the NRE the following year, and therefore drop out of the allocation procedure or not. The official phase then starts, excluding dropouts.

preferences that candidates introduced during the simulation phase.⁸ This system allows candidates to make their decision while being aware of the remaining vacancies, and of whether they have a chance of getting their preferred residency position.

Groups of candidates who wish to choose their residency positions jointly have the possibility to do so. Most often, these groups are composed of two individuals—presumably couples—who wish to do their residency in close proximity to each other. In that case, the group member with the best rank must declare to the CNG the rank of the candidate that he or she wants to choose with. Thereafter, we refer to candidates giving up on their initial rank as *downgraders*. During the final allocation process, downgraders pick their residency position at their new declared rank.⁹

After all medical students have selected their residency position, the specialisation stage starts and lasts for up to five years, depending on their choice of specialty.¹⁰ At the end of their specialisation, all students must submit a thesis to be allowed to practice as physicians.

2.2 Data on the National Ranking Examinations

The first dataset used in this paper is the list of students who took the NRE between 2004 and 2021. It associates each student to his or her exam rank and final allocation to a residency position (that is, a specialty and a location). The second dataset that we use gathers information on the number of vacancies offered each year for each position. We construct these datasets using information published each year by the Ministry of Health via Ministerial Orders in the Official Journal of the French Republic. After merging them, the dataset contains the exam year, rank and final allocation of each candidate, as well as the vacancies which are available to each candidate at their time of choice, given the vacancies that candidates with a better rank have picked already. We are therefore able to identify the occupational choice set faced by each candidate at the time of choice. We also have non-comprehensive information on marital status, for women only. Year of birth is also included for some years.

Thereafter, *subdivision* and *location* are used interchangeably, and refer to a geographical area comprising one or several teaching hospitals;¹¹ *position* refers to a medical specialty, location pair; and *vacancies* refer to the number of available slots offered within a position.

The sample of analysis used in this paper is obtained after imposing the following restrictions. First, we exclude the NREs which took place before 2010, because we do not perfectly observe allocation to

⁸If a candidate cannot physically be on her computer at her time of choice, then her highest available position from the official simulation phase is automatically picked by the software.

⁹After the NRE choice, and for the following instances for which the exam rank matters (e.g. internship choices), downgraders use their initial rank back.

¹⁰Under certain conditions, students are allowed to change specialty during their specialisation. The conditions are (i) to do it just once, (ii) that the change occurs within the same subdivision, (iii) that the intern could have gotten the newly chosen specialty in that subdivision on allocation day, given his/her rank, and (iv) that the change be requested before the end of the fourth semester of the residency, at the latest. From 2010 to 2012, the share of students who changed specialty after the NRE allocation ranged from 3.6 to 4 percent of the cohort's population only (Golfouse and Pheng, 2015).

¹¹The 26 subdivisions of continental France are shown in Figure A1 of the Appendix. There are two additional subdivisions in overseas France: Antilles-Guyane and Océan Indien.

specialties for the years 2004 to 2009.¹² Second, we focus on the individuals who are allocated to a residency position.¹³ Third, we exclude individuals who decide to work in overseas France, arguing that this small group of individuals might differ substantially from the main group. Finally, we drop individuals who choose to specialise in emergency medicine for the sake of across-year comparability, given that this specialty was not available before 2017. We are left with a sample of 88,294 individuals across 12 exam years.

Table 1 provides descriptive statistics on the National Ranking Examinations between 2010 and 2021. It shows that each year, 8,119 vacancies are offered for 8,280 candidates on average. It also shows that close to 59 percent of NRE takers are women and that candidates are 25 years old on average. Men taking the exam are slightly older than women, but the population is very homogeneous in terms of age (standard deviation of 2.0).¹⁴

Figure 1 displays the distribution of the rank obtained at the NRE by the men and women in our sample. It shows that men and women differ in their performance at the NRE. Men are more concentrated than women both at the top and at the bottom of the distribution, while women are more concentrated between these two extremes. Importantly, both men and women are present in all parts of the distribution. This figure only shows that while the sample is composed of 59 percent of women on average, this share is lower both at the bottom and at the top of the distribution (50.1 and 51 percent, respectively).

2.3 Data on Occupational Characteristics

This paper estimates and explains gender differences in self-selection into occupations among young physicians. After documenting these gender gaps, and in order to identify the job attributes which attract men and women differently, we characterise each medical specialty using relevant characteristics, such as expected earnings, hours worked, frequency of night shifts, and further perceived attributes such as the level of competition or the social contribution of the job. Below, we describe the different data sources from which we obtain these pecuniary and non-pecuniary characteristics.

2.3.1 Expected Earnings

The French healthcare system is universal and largely financed by the national health insurance, which is compulsory and contribution-based. Physicians can work in the public sector (46 percent in 2017, among which 66 percent are employed by a hospital), in the private sector (43 percent), or in both simultaneously.

¹²The reason is that during the years 2004 to 2009, allocation to specialties was performed in two steps and only the first step of the choice was recorded. From 2010 onwards, the procedure was changed and the two steps were merged.

¹³Each year, there are fewer allocated individuals than takers, and this is the case for two reasons. First, once an individual gets his final allocation, he can under some conditions decide not to take his position, and take the exam again the following year. Second, since students take the NRE before knowing if they met all the requirements necessary to pass the sixth year of medical studies, some of them end up failing it and therefore not being allowed to enter specialisation. All in all, over the period, between 88 and 98 percent of takers were allocated to a position.

¹⁴Note that the first, nineteenth, and ninety-ninth percentiles of age are equal to 23, 27, and 34, respectively.

Table 1: Descriptive statistics on the NRE between 2010 and 2021.

	(1) All	(2) Women	(3) Men	(4) Diff.	(5) Obs.
Nb vacancies	8,118.9 (583.177)				
Nb takers	8,279.9 (596.715)	4,846.3 (344.854)	3,433.6 (331.259)	1,412.75	
BEFORE SAMPLE SELECTION					
% Women	0.586 (0.492)				99,359
Age	25.2 (1.989)	25.0 (1.825)	25.4 (2.176)	-0.405***	72,772
Rank	4,161.1 (2,424.413)	4,179.0 (2,352.291)	4,135.7 (2,522.972)	43.240***	99,359
AFTER SAMPLE SELECTION					
% Women	0.593 (0.491)				88,294
Age	25.2 (1.971)	25.0 (1.821)	25.4 (2.148)	-0.394***	65,263
Rank	3,993.8 (2,425.834)	4,028.8 (2,344.974)	3,942.8 (2,538.155)	85.915***	88,294

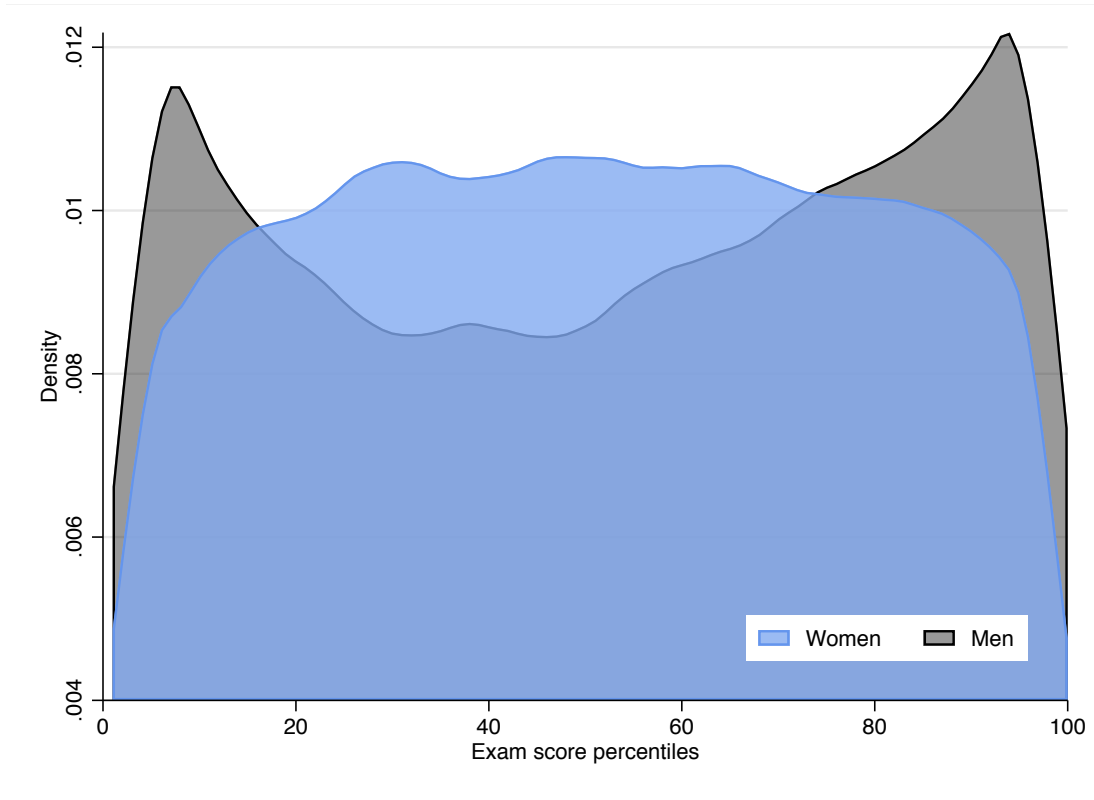
Notes: This table reports some descriptive statistics on the National Ranking Examinations between 2010 and 2021. *Nb vacancies* and *Nb takers* respectively report the number of vacancies that are offered on a given year on average, and the number of candidates taking the exam on a given year on average. The table reports the average value for the whole sample (1), the sample for men (2) and the sample for women (3), as well as the difference between the men and women averages (4) and the number of observations (5). Additionally, standard deviations for the means are reported in parenthesis, and significance levels of the two-sample t-tests for the difference in means between men and women are reported using *** p<0.01, ** p<0.05, * p<0.1.

In the public sector, earnings are set by a salary grid depending on qualifications and seniority. The rates set by this grid vary only marginally across specialties. However, physicians working in the private sector face a more flexible payment scheme. Precisely, their earnings mostly come from the fees they charge to their patients for each procedure they perform. All the medical procedures have a conventional fee, which is set by the Social Security and on which patients are partially or totally reimbursed depending on their health insurance scheme. Additionally, a group of physicians, called Sector 2, is allowed to charge a markup over this conventional fee as long as it is done “with tact and moderation”.¹⁵ All in all, the fees of private physicians, and therefore their earnings, vary greatly both within and across medical specialties and geographical areas.

To compute expected earnings, we combine three data sources from 2016. First, aggregated data from the French National Health Insurance Fund (CNAMTS) on earnings in the private sector by specialty of practice. Second, hospital salary grids provided by the Ministry of Health via Ministerial Orders in the

¹⁵Article R4127-53 of the French Public Health Code: “A physician’s fees must be fixed with tact and moderation, taking into account the regulations in effect, the procedures which are performed, or potential special circumstances.”

Figure 1: Exam score distribution by gender.



Notes: This figure plots the exam score distribution density for women and men who took the NRE and were allocated to a residency position between 2010 and 2021. It relies on data collected from the Official Journal of the French Republic.

Official Journal of the French Republic. Third, data provided by the Directorate for Research, Studies, Evaluations and Statistics (DREES) on the demographics of physicians in the private and public sectors by specialty of practice. Combining these data sources, we define expected earnings in a given specialty as the average, cross-sector yearly earnings in that specialty, weighted by physician population in each cell.¹⁶ We merge this data to the NRE file using information on specialty.

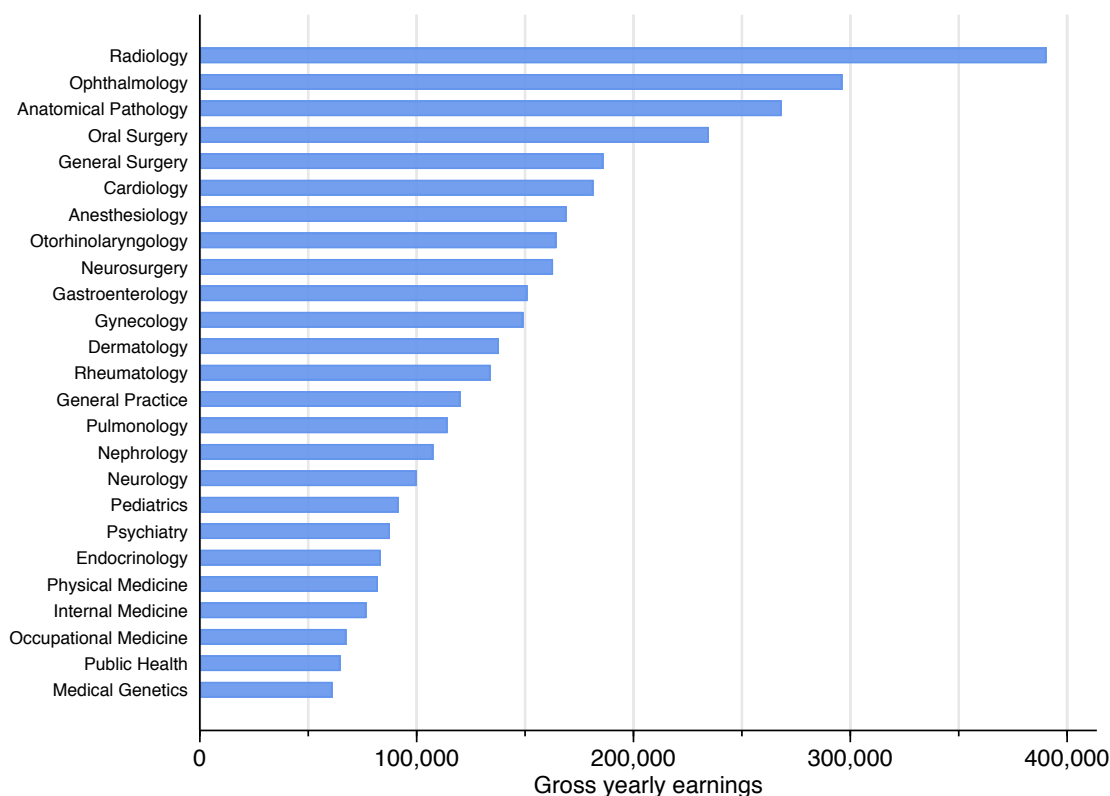
Figure 2 plots our proxy for yearly gross expected earnings by specialty. It shows that there is significant variation in expected earnings across specialties, our proxy ranging from only slightly more than 60,000 euros in public health and medical genetics to close to 390,000 euros in radiology.

2.3.2 Time Requirements

Turning to non-pecuniary characteristics, one of the most prominent job attributes for which men and women are likely to differ in their preferences is their work’s time requirements. In the medical context, two measures that are particularly relevant are the duration of the work week and the number of night shifts. Like salaries, hours worked and night shifts are subject to strict regulations: residents can work

¹⁶We are currently working on improving this proxy for expected earnings using an administrative panel data on physicians earnings.

Figure 2: Expected yearly earnings by specialty.



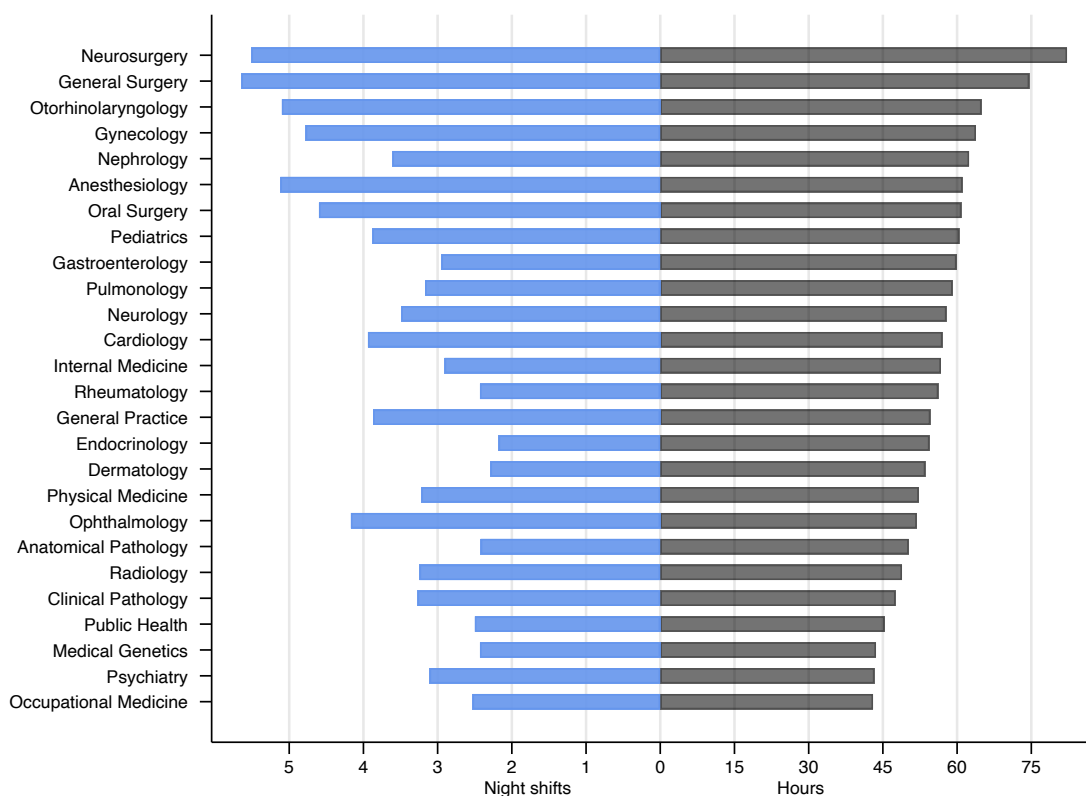
Notes: This figure shows the yearly gross earnings that physicians can expect to earn in each specialty on average. This measure combines aggregated data on the earnings of private physicians provided by the CNAMTS and hospital salary grids collected from the Official Journal of the French Republic, which are averaged and weighted by population using data on demographics provided by the DREES.

a maximum of 48 hours and participate in maximum one night shift per week.¹⁷ To obtain variation across specialties in these two significant job attributes, we use declared hours and number of night shifts worked by medical residents. This information is obtained from two surveys, which were conducted by the largest trade union in the healthcare sector (ISNI) on a representative sample of between 20 and 25 percent of active residents in 2019 and 2012, respectively. We link this information to the NRE data using specialty of practice.

Figure 3 plots the average number of hours worked in a week and the number of night shifts worked in a month by residents in each specialty. It highlights the variation that exists in these two dimensions across specialties: residents in neurosurgery and general surgery report working almost twice as many hours as those in psychiatry and occupational medicine. Similarly, residents in general surgery do more than 5 night shifts a month, while those in endocrinology do 2.

¹⁷Decree number 2015-225 from February 26, 2015.

Figure 3: Time requirements by specialty.



Notes: This graph shows the average number of hours worked in a week by medical residents in each specialty (left panel) and the average number of night shifts performed in a month by medical residents in each specialty (right panel). Data used comes from two different surveys conducted to a nationally representative sample of residents in 2019 and 2012, respectively, by the trade union ISNI (*InterSyndicale Nationale des Internes*).

2.3.3 Other Perceived Characteristics

The Occupational Information Network (O*NET) database contains hundreds of occupation-specific characteristics on a large number of occupations, including several medical specialties. Specifically, it gathers information on the knowledge, skills, and abilities required in each occupation, as well as on the activities and tasks performed, and their importance in each occupation. It also contains information on the context in which work is done, and on the values that are important in each occupation. Importantly, this data is collected via interviews to random samples of workers in each targeted occupation in the United States. One might worry that knowledge, work conditions and work values are likely to differ across countries. Even though we acknowledge that absolute differences in these characteristics across specialties are likely to differ between France and the U.S., we claim that *relative* differences should be rather stable between the two.

To link the O*NET and NRE data, we manually search the relevant medical specialties in the O*NET database, and find a match for 92.5 percent of our sample.¹⁸ Following Cortes and Pan (2017), we create

¹⁸Specifically, we fail to match cardiology, hematology, legal medicine, nephrology, oncology, and otorhinolaryngology.

four composite indices to characterise the different medical specialties, as described in Table A1 in the Appendix. First, we select the O*NET measures which we find both relevant in our setting, and likely to be comparable in the U.S. and French contexts. We normalise each measure to have a mean of zero and a standard deviation of one in the sample of medical specialties, and then take the average of the normalised measures. We obtain four indices (competition, social contribution, time pressure, and interactional skills), which we use to characterise the occupations into which men and women self-select.

3 Gender Differences in Occupational Choices

In this section, we first describe the empirical strategy that we use in order to analyse gender differences in occupational choices, and then expose our estimation results.

3.1 Empirical Strategy

To isolate the role of job seekers' preferences in the determination of gender-based occupational segregation, the ideal experiment would compare the occupational choices of individuals with similar characteristics (education, experience, ability, etc.) who face no screening by employers and the same occupational choice set, and who differ only in their gender. The setting provided by the National Ranking Examinations is very close to that one. It not only removes the role played by employers in the hiring process, but also allows to observe (i) each individual's occupational choice, (ii) the rank of that individual in the population of candidates of a given year, and (iii) the number of vacancies offered per position in a given year. Taken together, these elements allow to retrieve each candidate's exact occupational choice set, and thus to compare the decisions of candidates facing the same pool of available positions.

To further identify the role of job seekers' preferences, we split our sample in a way that distinguishes between constrained and unconstrained choices. Precisely, we define as *unconstrained* those individuals who make their occupational decision when 99 percent or more of all positions are still available. The *constrained* group thus includes all the individuals who choose their position when less than 99 percent of all positions are available and who have the possibility to choose the specialty under study (that is, who have a rank which is lower or equal than the rank of the last candidate selecting that specialty). We provide a set of alternative definitions for being unconstrained in Appendix B.2.

Throughout, we estimate the following equation using a variety of outcome variables:

$$y_i = \beta female_i + \gamma_{c(i)} + \epsilon_i \tag{1}$$

where i refers to a candidate in a given year, y_i is the outcome variable under study for candidate i , $female_i$ is an indicator variable taking the value 1 if candidate i is a woman and 0 otherwise, $\gamma_{c(i)}$ are

choice set fixed effects, and ϵ_i is an error term with standard properties. We define choice set fixed effects as groups of five individuals with consecutive ranks. These fixed effects allow to control for group-specific characteristics, such as exam performance (which can be seen as a combination of individual ability and effort) and, most importantly, the set of available positions to choose from. Figure A2 in the Appendix offers an overview of the vacancy filling process for each specialty over the exam score distribution. It shows that some specialties are filled sooner than others, and justifies conditioning on choice set to estimate gender differences as well as focusing on candidates at the top of the exam score distribution. Appendix B.1 shows that our results are robust to different definitions of choice set fixed effects.

We start by estimating linear probability models separately on the samples of constrained and unconstrained candidates, using as the outcome an indicator variable taking the value 1 when a given medical specialty s is chosen by candidate i and 0 otherwise. To provide a more complete view of gender differences in preferences for each specialty, we also estimate equation (1) at different positions of the exam score distribution, and report the results in Figure A3 in Appendix A.

3.2 Results

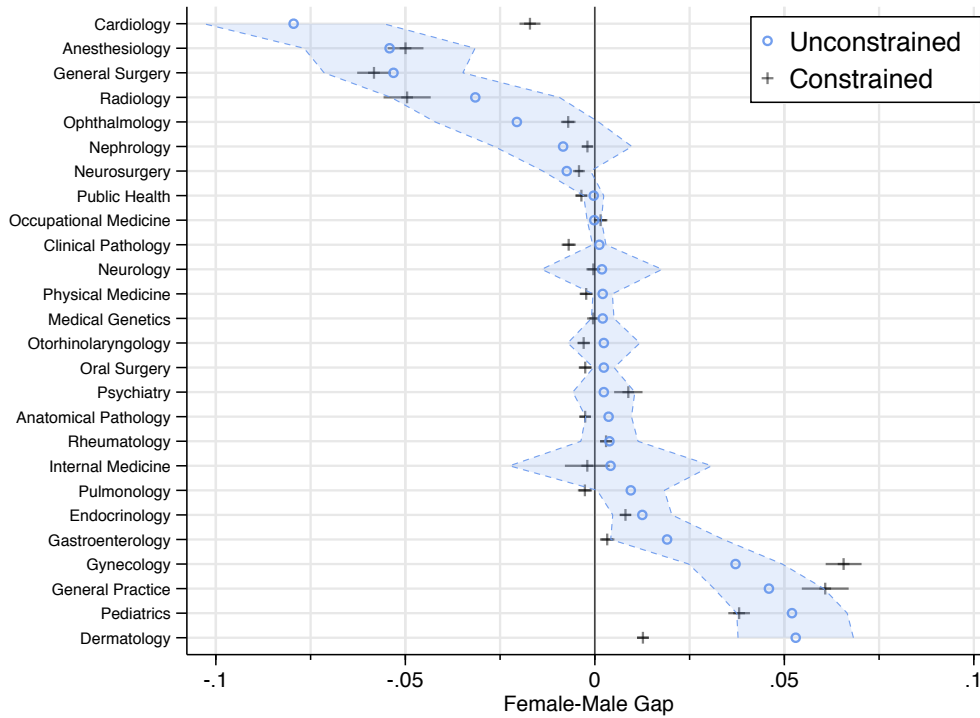
Figure 4 plots gender differences in the propensity to self-select into specialties, separately for the unconstrained and constrained groups of candidates. Precisely, each row reports the coefficient $\hat{\beta}$ and its 95% confidence interval estimated from equation (1) using an indicator variable taking the value 1 if candidate i chooses the specialty under consideration and 0 otherwise. We estimate each linear probability model separately for the unconstrained and constrained group of candidates. As a result, each dot can be interpreted as the gender difference in the probability of self-selecting into a given specialty, conditioning on position availability.

The first result provided by Figure 4 is that men and women facing similar occupational choice sets make very different choices. Women are significantly more likely than their male counterparts to choose endocrinology, gastroenterology, gynecology, general practice, pediatrics, and dermatology. Symmetrically, men are significantly more likely than their female counterparts to pick ophthalmology, radiology, general surgery, anesthesiology and cardiology. This result holds for constrained candidates and, strikingly, for unconstrained candidates, who can choose any specialty in any location. Women at the top of the performance distribution are 7.4 percentage points less likely to choose cardiology, 5.4 percentage points less likely to choose anesthesiology, and 5.5 percentage points less likely to choose general surgery. Symmetrically, they are 3.7 more likely to self-select into gynecology, 4.4 percentage points more likely to self-select into general practice, 5.4 percentage points more likely to choose pediatrics, and 5.4 percentage points more likely to choose dermatology than their male counterparts facing the same choice set.

These results allow to go one step further compared to the results obtained on the constrained group of

candidates. They imply that men and women facing the same choice sets *prefer* different occupations: even when they are unconstrained in terms of the positions that they can choose from, men and women still decide to work in different occupations. It suggests that differences in preferences for job characteristics are a key component behind the gender differences in self-selection.

Figure 4: Gender gap in self-selection into specialties.



Notes: This figure plots the coefficients $\hat{\beta}$ and 95% confidence intervals estimated from equation (1), separately for constrained and unconstrained individuals, and for 26 medical specialties. Negative (positive) values indicate that, on average, women are less (more) likely to self-select into the corresponding specialty than men with a virtually identical choice set. Unconstrained students are those who select a residency position when 99 percent of all positions are still available in the selection process. Constrained students are those who choose their residency position when less than 99 percent of all positions are available and for whom the specialty under study is still available (that is who have a rank which is lower or equal than the rank of the last student selecting that specialty). All the gender gaps are estimated using OLS and include choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. The shaded area (unconstrained sample) and horizontal solid black lines (constrained sample) show 95% confidence intervals using heteroskedastic robust standard errors.

Figure A3 in the Appendix highlights that the gender gap in the probability of self-selecting into each specialty varies greatly along the exam score distribution. We specifically observe an inverse U-shaped relationship between the estimates and the exam score for general practice, gynecology, and pediatrics, and a U-shaped relationship for anesthesiology, radiology, and general surgery. It suggests that, for these specialties, the gender gap in self-selection patterns is larger towards the middle of the exam score distribution than at the top. The two extreme examples are general practice and surgery. While women in the top 5 percent of the performance distribution are 4 percentage points more likely to choose general practice than the men in the same percentiles, women between the 50th and the 60th percentile are 13 percentage points more likely to choose general practice than their male counterparts facing the same choice set. Symmetrically, while women in the top 5 percent of the exam score distribution

are 7 percentage points less likely to choose general surgery than men, women between the 50th and the 60th percentile are 17 percentage points less likely to choose surgery than their male counterparts with the same pool of available positions.¹⁹

This suggests that as we move down the exam score distribution, and thus as vacancies get filled, gender differences in occupational choices are exacerbated. This result opens the door for an additional class of explanations for the gender differences in self-selection patterns: the existence of gender differences in how to face the occupation-location trade-off which emerges as positions are filled. In the remaining sections, we provide evidence on the mechanisms that are behind the gender gaps in self-selection probabilities highlighted above.

4 Gender Differences in Preferences for Job Characteristics

In this section, we analyse gender differences in preferences for job attributes. To do so, we use expected yearly earnings, number of night shifts and hours worked, time pressure, level of competition, social contribution, and interactional skills required to perform the job. We are particularly interested in the gender differences that might exist at the top of the exam performance distribution, where we have argued that choices are unconstrained.

4.1 Gender Differences in Preferences for Expected Monetary Gains

To study whether expected earnings attract men and women differently, we identify the position of the specialty selected by each candidate in the gross earnings distribution, and define 10 indicator variables taking the value 1 if the specialty selected by candidate i has expected earnings falling in the corresponding decile of the expected gross earnings distribution and 0 otherwise. We estimate equation (1) for the 10 deciles of the earnings distribution, separately for the constrained and unconstrained groups. The coefficient on the *female* variable thus measures the difference between the propensity of women and men to self-select into a specialty that belongs to a certain decile of the expected earnings distribution, conditional on these candidates facing the same choice set.

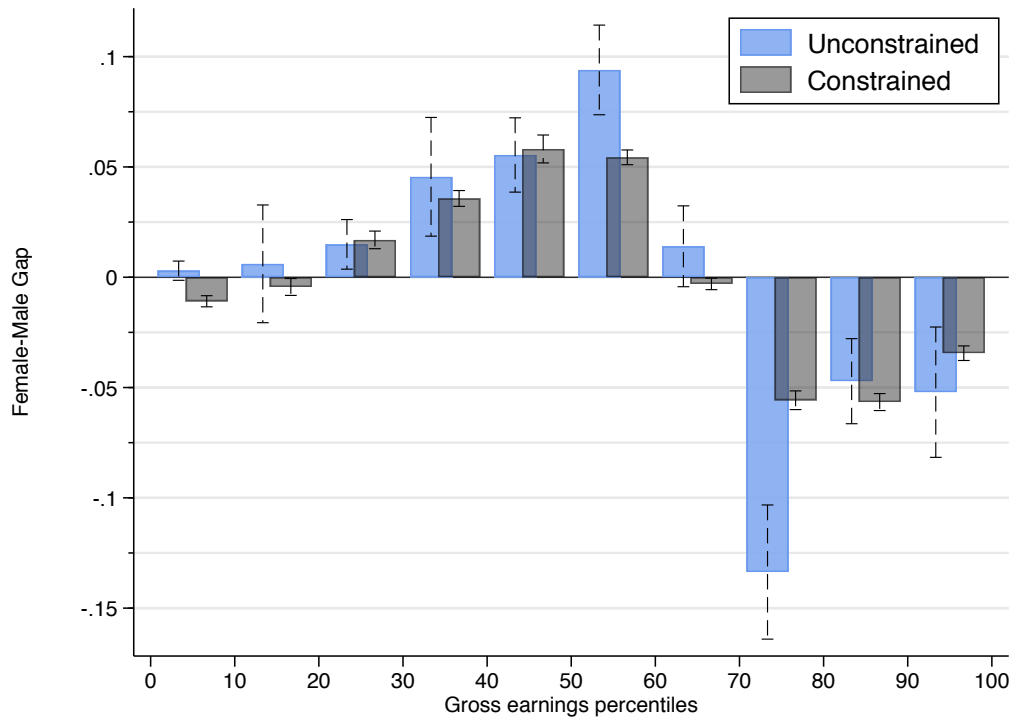
The results are displayed in Figure 5. We find that women are on average less likely to prefer specialties with expected gross earnings belonging to the upper 30 percent of the gross earnings distribution than men facing the same pool of available positions. This is true for unconstrained individuals, of whom we observe the preferred position, as well as for constrained ones. In contrast, women are more likely than men to select occupations with expected earnings that are between the 20th and 60th percentile of the gross earnings distribution. Specifically, unconstrained women are 13 to 5 percent less likely than their

¹⁹The gender gap in the probability of self-selecting into a given specialty systematically tends to zero when approaching the lower parts of the exam score distribution. This effect is mostly mechanical: as the vacancies for a given specialty get filled, candidates cannot self-select into that specialty anymore, and therefore gender gaps are reported as 0.

male counterparts to prefer occupations with expected gross earnings belonging to the 70th and 100th percentiles of the gross earnings distribution, while these figures range from 5 to 3 percent for constrained women.²⁰

The fact that, in most parts of the earnings distribution, the coefficients estimated on the unconstrained sample are larger than those estimated on the constrained sample suggests once again that supply side factors play a very relevant role in explaining observed gender differences in occupational decisions.

Figure 5: Gender gap in selection on gross expected earnings.



Notes: This figure shows the gender gaps in the probability of self-selecting into a residency position that falls in each of the deciles of the gross earnings distribution. Negative (positive) values indicate that women are less (more) likely to self-select into specialties with higher expected earnings than their male counterparts. Expected earnings is defined as the weighted average of earnings in the private and hospital sectors, by specialty. Individuals choosing their specialty when 99% or more of the residency positions where still vacant are labeled as unconstrained, while the rest as constrained. All the gender gaps are estimated using OLS and include choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. Dashed vertical lines show 95% confidence intervals using heteroskedastic robust standard errors.

4.2 Gender Differences in Preferences for Non-Monetary Attributes

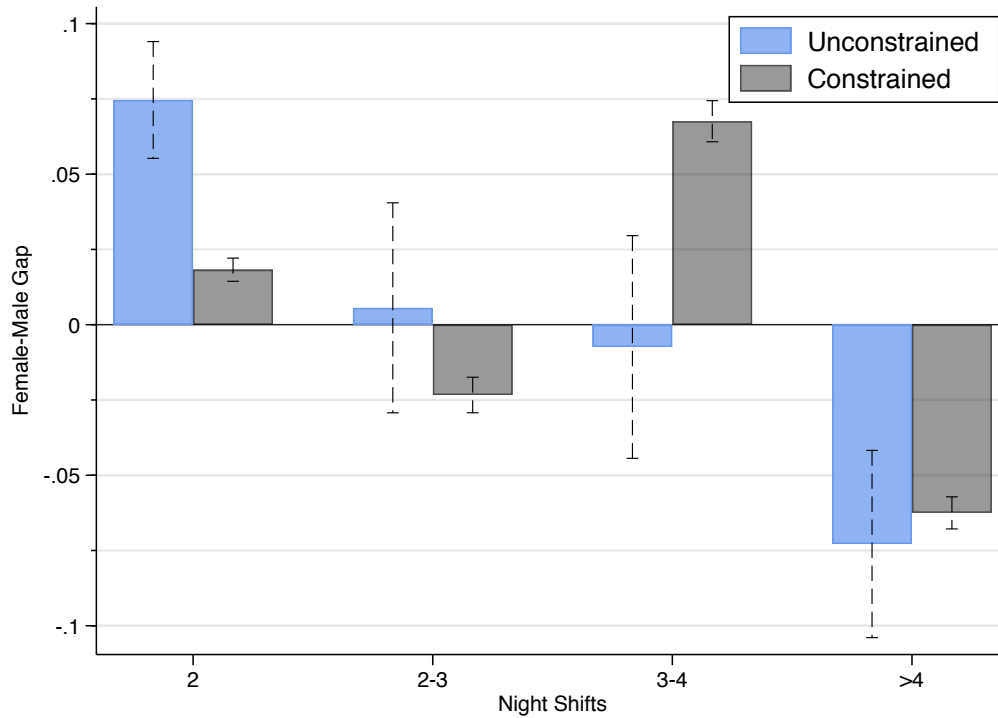
We then turn to estimating the gender gaps in preferences for the non-pecuniary dimensions of the occupation decision. We split the distribution of hours worked and night shifts performed in quartiles, and then proceed as in section 4.1. To do so, for each occupational characteristic, we define four indicator variables taking value 1 if the characteristic under study (hours worked, number of night shifts) observed

²⁰A very similar pattern of results is found when using non-hospital gross earnings instead of overall gross earnings as reported in Figure A4 in the Appendix.

in the specialty chosen by individual i belongs to the corresponding quartile of its distribution and to 0 otherwise. We then estimate equation (1) using linear probability models and the indicator variables defined above as the dependent variables, separately for the constrained and unconstrained samples. We report the results in Figures 6 and 7.

Figure 6 shows that the higher the number of night shifts required by a medical specialty, the less likely unconstrained women are to self-select into that specialty compared to their male counterparts. This result highlights the fact that women at the top of the performance distribution have a stronger preference for temporal flexibility than men at the top of the distribution. This result is striking, given that the unconstrained sample contains the most able and motivated candidates. The results are less conclusive when it comes to the constrained sample. We argue that it is likely to be driven by a hidden heterogeneity along the rank distribution.

Figure 6: Gender gap in selection on night shifts.

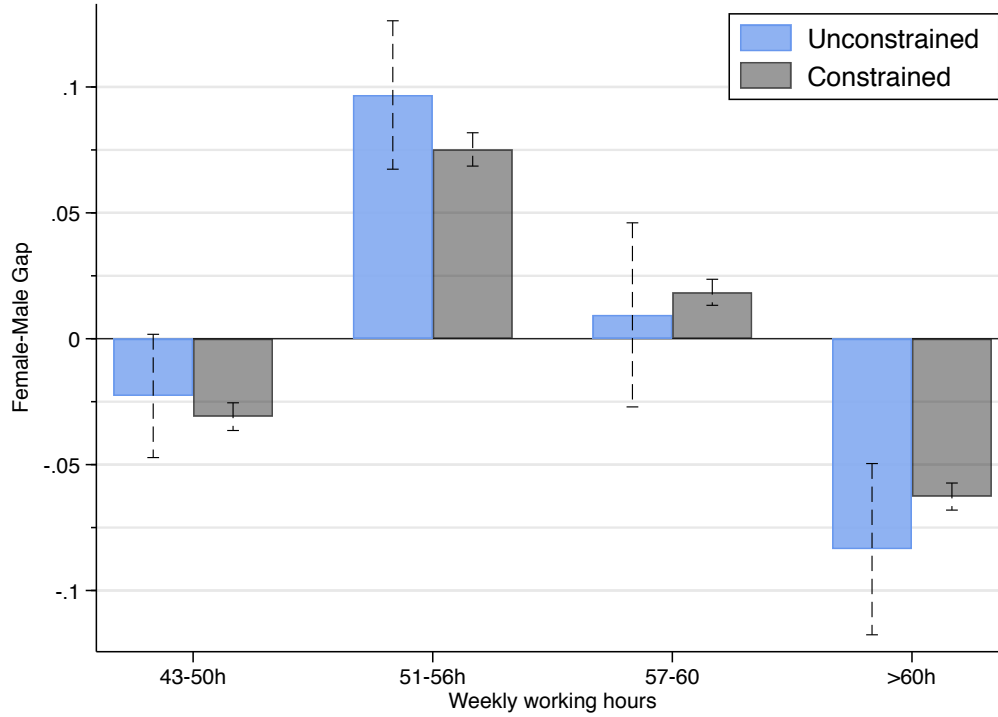


Notes: This figure plots gender gaps in the probability of females selecting a specialty that falls in each quartile of the monthly night shifts distribution, separately for the so called unconstrained and constrained individuals. Negative (positive) values indicate that, on average, women are less (more) likely to self-select into specialties with the corresponding attribute than men with a virtually identical choice set. Individuals choosing their specialty when 99% or more of the residency positions where still vacant are labeled as unconstrained, while the rest as constrained. All the gender gaps are estimated by OLS and include choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. Dashed vertical lines show 95% confidence intervals using heteroskedastic robust standard errors.

Figure 7 shows that both constrained and unconstrained women are less likely than men to self-select into jobs which have the lowest number of hours worked (first quartile of the distribution). Then, both constrained and unconstrained women are much more likely than men to self-select into occupations in the second quartile of the hours worked distribution. The gender gap is then smaller (and even insignificant

in the unconstrained group) in the third quartile of the distribution. Last, women are much less likely than men to self-select into occupations which are at the top of the hours worked distribution. It suggests that very long hours discourage women much more than men, in both the constrained and unconstrained groups.

Figure 7: Gender gap selection on working hours.

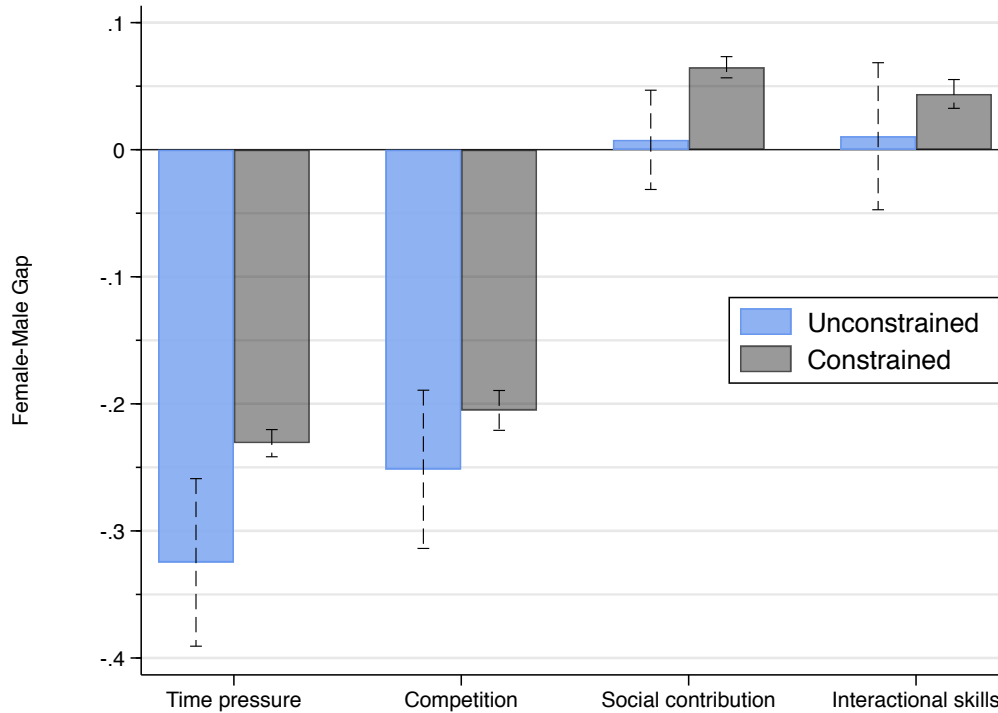


Notes: This figure plots gender gaps in the probability of females selecting a specialty that falls in each quartile of the weekly hours distribution, separately for the so called unconstrained and constrained individuals. Negative (positive) values indicate that, on average, women are less (more) likely to self-select into specialties with the corresponding attribute than men with a virtually identical choice set. Individuals choosing their specialty when 99% or more of the residency positions were still vacant are labeled as unconstrained, while the rest as constrained. All the gender gaps are estimated using OLS and include choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. Dashed vertical lines show 95% confidence intervals using heteroskedastic robust standard errors.

Finally, we estimate (1) using the occupational characteristic under study as defined in Table A1 and observed in the specialty chosen by individual i as the outcome variable. We estimate linear probability models on the constrained and unconstrained samples, and report the results in Figure 8. It shows that women are more likely to shy away from occupations which impose time pressure and a competitive environment than their male counterparts. This is true both in the constrained and unconstrained samples. However, only constrained women are more likely than their male counterparts to self-select into specialties that are more socially oriented and that require more interactional skills. The magnitude of these effects is much smaller than that of the effects on time pressure and competition.

All in all, we find that women who choose their position when all positions are still available are more likely to self-select into occupations in which the expected monetary gain is smaller, in which there is more time flexibility, and which have a more important social component than their male counterparts.

Figure 8: Gender gap in selection on O*NET characteristics.



Notes: This figure shows the gender gaps in the probability of selecting a specialty with a higher value in the relevant O*NET attribute. Negative (positive) values indicate that women are less (more) likely to self-select into specialties with the corresponding attribute than their male counterparts. Each index was re-scaled to have mean zero and a standard deviation of one. Individuals choosing their specialty when 99% or more of the residency positions are still vacant are labeled as unconstrained, while the rest as constrained. All the gender gaps are estimated using OLS and include choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. Dashed vertical lines show 95% confidence intervals computed using heteroskedastic robust standard errors.

These results show that preferences for certain job characteristics play an important role in explaining occupational segregation: even when facing no barrier to entry and the same choice set, men and women choose different occupations. However, note that we are not able to pin down the mechanisms leading to the formation of these preferences, as doing so would most likely require a well-defined experimental design, which is out of the scope of this paper. Women might prefer occupations which allow for more flexibility than those preferred by men not because they have an intrinsic taste for flexibility, but because of the gender roles imposed by social norms. Women might be less willing to self-select into ‘male occupations’ for the sole reason that it is not what is socially expected from them (Akerlof and Kranton, 2000), or because of the aversion that men might have to let women enter their occupations (Goldin, 2002). Moreover, women might refrain from entering inflexible occupations because they internalise the fact that they will be expected to juggle family and work (Goldin, 2004, 2006). Our estimates therefore capture a combination of all the factors which are intrinsic to job seekers and which drive them to sort into different occupations. We can however expect the impact of social norms to be somewhat smaller at the top of the performance distribution, where the most motivated and able candidates are.

5 Gender Differences in Preferences for Location

We turn to considering the second class of explanations that we have highlighted in section 3.2: gender differences in preference for location when facing the occupation-location trade-off, that is the trade-off faced by candidates whose preferred position has been filled at their time of choice, and who thus have to compromise in one of the two dimensions.

The decision on where to live and work is a crucial one for young individuals entering the labour force. On the one hand, given the duration of the residency program, NRE candidates select the location in which they are going to live for the next three to five years. On the other hand, the occupation dimension of the decision determines the field in which candidates are going to work during their whole career.

While previous research analysing location and labour market outcomes simultaneously has focused on gender differences in willingness to commute to the workplace,²¹ this setting gives the opportunity to study gender differences in two new dimensions of the location decision: the trade-off emerging from having to decide between one's preferred career path and one's preferred medium-term location, and the willingness to be mobile across the country. We leverage the benefits of the residency selection process and new data containing both revealed and stated preferences for residency positions, to investigate whether men and women differ in their preference for geographical mobility. We describe the data used for this analysis in details below.

5.1 Data on Stated Preferences for Residency Positions

Data on stated preferences for residency positions is collected during the simulation phase described in section 2.1. The simulation phase is the period between the moment when students get their exam rank and the allocation days. During this period, students introduce an ordered list of their preferred residency positions into an online platform operated by the CNG. Students can update their list at any time until their turn to choose their final residency position comes. This turn is determined by their exam rank. Crucially, students have no incentive to introduce in their list a residency position which they know they are not willing to select at their time of choice. Therefore, this list of residency positions can be seen as a candidate's true ordered list of preferences. As a result, we consider the positions which are inputted by a candidate into the online platform as *stated preferences* for these positions, and the positions which are selected on allocation days as *revealed preferences*.

During the simulation period, the platform records with high frequency the residency position that each candidate would obtain if the deferred acceptance algorithm was to operate at that moment. That is, it collects each student's first available position following the order dictated by their exam rank and pools them in a public list. This procedure is repeated every five minutes. The public list contains the exam

²¹See for instance [Le Barbanchon, Rathelot and Roulet \(2019\)](#) and [Fluchtmann et al. \(2020\)](#).

rank of each student, the position which is selected by the deferred acceptance algorithm for that student at that moment, and the rank of the selected residency position in the student’s list of preferences. We systematically recorded this public list every time it was updated for the years 2019 to 2021. As a result, we observe, at any time, a *simulated* allocation of candidates to residency positions, and the rank of this simulated position on each candidate’s list.²²

Although this information is not equivalent to observing each candidate’s full list of stated preferences for residency positions, it allows to make inference on the positions that each student is willing to take. We consider this information as a proxy for a candidate’s complete list of stated preferences.

We construct a dataset containing the list of all the unique positions (i.e., specialty and location) that were selected by the deferred acceptance algorithm at a given point in time for each candidate. In this dataset, each individual is observed as many times as there are unique positions that were selected for him or her by the algorithm during the simulation phase. Table A2 displays descriptive statistics for the 2019 to 2021 simulation phases, separately by gender. It shows that on average, men input more positions into the online platform than women, and that it is due to them inputting both more specialties and locations than women. It also shows that men are on average slightly more likely to downgrade than women.

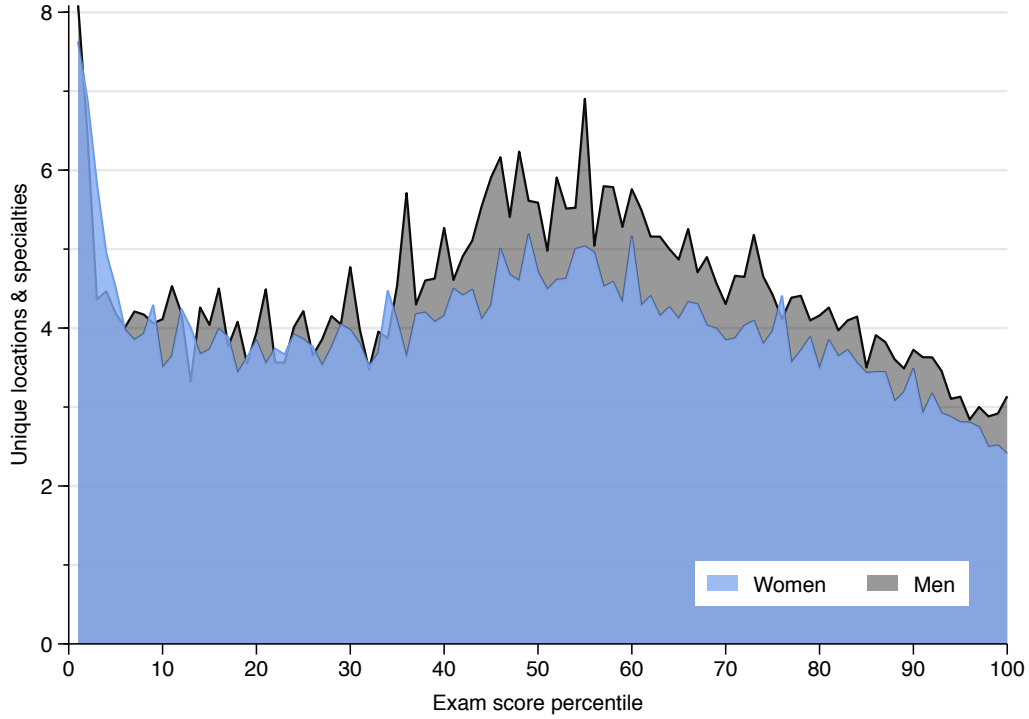
Figure 9 plots the average number of unique specialties and locations that were gathered for a given individual during the simulation phase, by percentile of the exam performance distribution. As expected, the number of unique positions that are obtained by the deferred acceptance algorithm is lowest at the top of the performance distribution. Moreover, these positions are on average ranked very high in their ordered list of preferences, as shown in Figure A5 in the Appendix. According to these two figures, the better ranked a student is, the more likely he or she is to get his or her preferred position, and therefore the less chances there are that we observe alternative desired positions. Then, moving down the exam score distribution, both measures increase until the fiftieth percentile, and then start to decrease. The figures show that on average, the deferred acceptance algorithm selects positions which are ranked relatively high on students’ lists of preferences, which suggests that most candidates end up working in positions which they rather like.

5.2 Results

We use the data on stated and revealed preferences for residency positions to investigate whether men and women differ in their preference for geographical mobility. We start by analysing the existence of a labour market feature that has seldom been studied: the trade-off between preferred occupation and preferred location. We approximate the measurement of this trade-off by comparing the number of unique

²²See Appendix C for a detailed description of the data collected from the CNG website.

Figure 9: Number of unique locations and specialties in candidates' list of preferences.



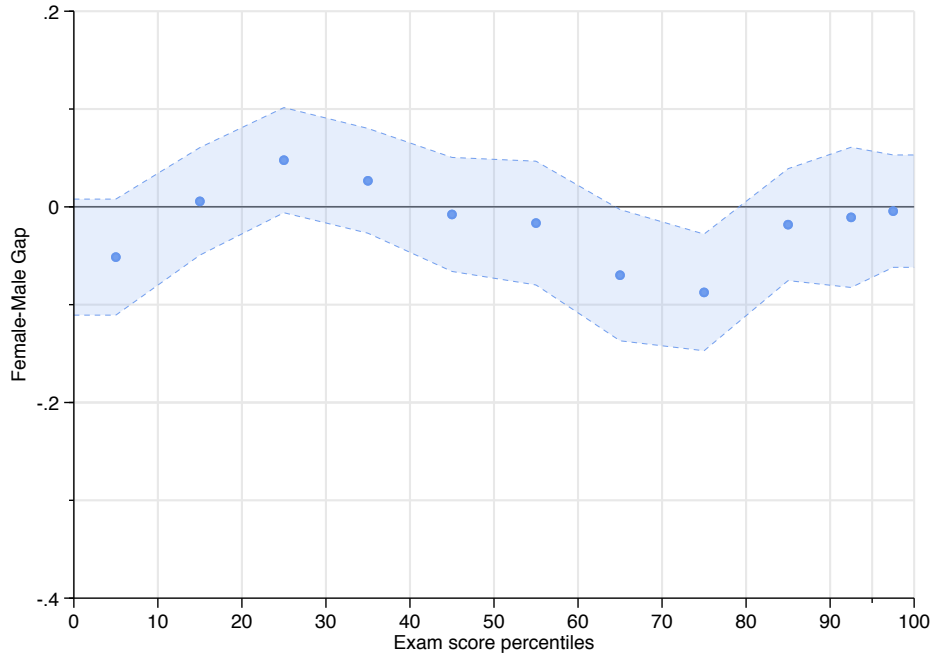
Notes: This figure plots the average number of unique locations and unique specialties as extracted by the deferred acceptance algorithm during the simulation phase. They are plotted over the percentiles of the exam performance distribution, for men and women separately.

locations and unique specialties that appear on each individual's preference list. We argue that the higher the number of unique locations relative to unique specialties, the less bound to a specific location the individual is. We thus compute the ratio of the number of unique locations to the number of unique specialties present in our proxy list of preferences. A ratio lower than one indicates that a candidate introduces less unique locations than unique specialties, and therefore suggests that he or she has a stronger preference for the location than the occupation dimension. Figure A6 in the Appendix shows that this ratio is strictly greater than 1 in all parts of the performance distribution and for both genders, showing that both men and women put more importance on occupation than on location, on average. We estimate equation (1) separately at different positions of the exam rank distribution using the log transformation of this ratio as the dependent variable, and show the results in panel (a) of Figure 10. The coefficients on the *female* variable thus capture the percentage difference in the propensity to be mobile that exist in the different deciles of the exam performance distribution between women and men facing the same choice set.

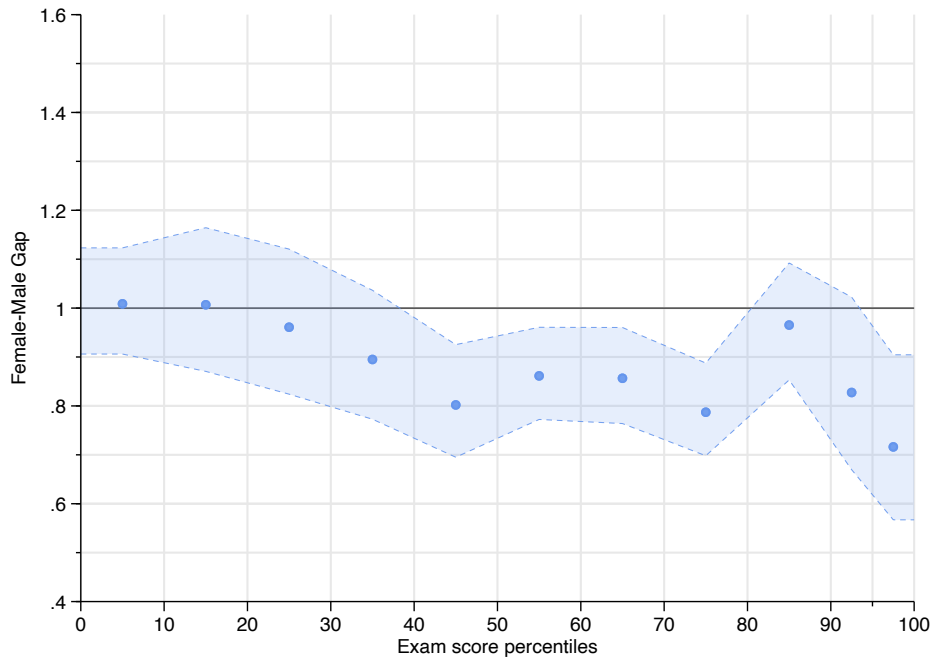
Panel (a) suggests that there is no gender gap in preference for mobility at the top of the exam score distribution. This is an expected result, given that top exam performers are not constrained in their choice, and thus do not face the occupation-location trade-off that this ratio captures. Moving down

Figure 10: Gender gap in preferences for location.

(a) Ratio of unique locations to unique specialties.



(b) Spatial dispersion of preferred locations.



Notes: Panel (a) plots gender differences in the natural logarithm of the ratio of the number of unique locations to the number of unique specialties extracted by the deferred acceptance algorithm during the simulation phase. Negative (positive) values indicate that on average a lower (higher) ratio is observed for women than for men with virtually equivalent choice sets. Panel (b) plots the estimated incidence rate ratio comparing women to men in terms of spatial dispersion of their preferred unique locations extracted by the deferred acceptance algorithm during the simulation phase. Estimates are produced by estimating equation (1) using Poisson pseudo maximum likelihood and a measure of spatial dispersion as the dependent variable. Values below (above) one indicate that on average a lower (higher) spatial dispersion of desired locations is observed for women than for men with virtually equivalent choice sets. All the gender gaps are conditional on choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. The shaded area shows 95% confidence intervals computed using heteroskedastic robust standard errors.

the performance distribution, being a woman becomes associated with having a 9 percent lower ratio of unique locations to unique specialties in the platform’s list. This result suggests that as positions get filled—triggering the emergence of an occupation–location trade-off—women put more weight than men on the location dimension, even though both genders still care more about the occupation dimension, as shown by Figure A6. This gender difference fades away as even more positions are filled.

Our interpretation is that the trade-off that the best constrained candidates face is different from the one faced by the rest of the constrained group. The trade-off faced by the former is likely to be between their preferred occupation and their preferred location. Our results suggest that in that case, women have a stronger attachment to location than men. However, when the rest of the constrained candidates choose, it is very likely that their preferred specialty has already become unavailable. Hence, they might have to pick a position which is sub-optimal both in terms of occupation and in terms of location, and therefore face a trade-off with lower stakes. We interpret these results as suggestive evidence of a stronger attachment to a particular location for women than men, when getting one’s preferred location might come at the cost of not getting one’s preferred occupation.

To complement the first analysis, we turn to looking at the spatial dispersion of the locations extracted by the deferred acceptance algorithm for a given individual. To do so, we first record the latitude and longitude of the centroid of each unique location extracted by the algorithm. We obtain two column vectors of individual-specific length L , X_i^1 and X_i^2 , whose l th components are the latitude and longitude of individual i ’s l th preferred location’s centroid, respectively. We then compute the variance of X_i^1 and X_i^2 , and sum them to obtain a measure of total dispersion of $X_i = (X_i^1, X_i^2)$.²³ Intuitively, we interpret the sum of the variance of the two coordinates of a student’s desired locations as a measure of his or her propensity to be mobile for the residency placement.

To capture the gender gap in candidates’ propensity to be mobile, we estimate equation (1) with Poisson pseudo maximum likelihood (PPML) using the sum of variances defined above as the dependent variable.^{24,25} Panel (b) of Figure 10 plots the estimated gender differences in terms of incidence rate ratios that exist along the exam score distribution. We find that the locations extracted by the deferred acceptance algorithm for women in the top 60 percent of the exam score distribution have a 0.7 to 0.85 greater rate ratio than the locations extracted for men with virtually identical choice sets. These rates translate into 30 to 15 percent times *lower* geographical dispersion of the locations introduced by women

²³Suppose $X_i = (X_i^1, X_i^2)$ is a random variable that take values on \mathbb{R}^2 for each individual i . Then $Var(X_i^1) + Var(X_i^2)$ can be interpreted as a measure of total dispersion of X_i .

²⁴Three main reasons motivate the use of PPML as opposed to a log-linearised model fit by ordinary least squares (OLS): first, PPML provides a natural way of dealing with the large number of zeros that characterises our non-negative dependent variable (Correia, Guimarães and Zylkin, 2020). Second, parameters estimated with log-linearised models fit by OLS are inconsistent in the presence of heteroskedasticity (Silva and Tenreiro, 2006). Third, PPML does not require to assume that our dependent variable follows a specific distribution.

²⁵To estimate PPML models with the high dimension fixed effects that we use to control for position availability—groups of five individuals with consecutive exam ranks—we implement the newly developed approach by Correia, Guimarães and Zylkin (2020).

in their proxy list of preferences.

Note that this difference in spatial dispersion is largest in the group of unconstrained individuals, at the very top of the exam score distribution. No statistically significant difference is found for students in the lower 40 percent of the exam score distribution. These estimates suggests that, compared to men, women tend to introduce in their list of preferences locations which are geographically closer to each other. This result has two potential explanations. First, women might be less willing than men to move across the country for their residency. Second, the specialties which are targeted by women might be less demanded than those targeted by men, and thus women might not need to be as mobile as men.

In order to have a better understanding of which of these two mechanisms is at play, we replicate the two previous analyses excluding all the individuals for which General Practice (GP) is observed in their list of preferences. General practice is by far the specialty that offers the largest number of vacancies, 40 percent of vacancies offered over the 2019-2021 period being for GP positions. Students who want to become general practitioners can therefore do so in virtually any of the 26 subdivisions. Consequently, these students are likely to introduce less alternative desired locations in their list of preferences, resulting in a lower number of unique observed locations. This would not be a problem if GP was selected at the same rate by men and women. However, Figure 4 shows that this is not the case, since unconstrained women are 4 percentage points more likely to choose general practice than unconstrained men.

The results of these verification exercises excluding candidates for which the deferred acceptance algorithm extracted GP at any point during the selection procedure are reported in panel (a) and panel (b) of Figure A7, respectively. Although most estimates' magnitude change and are less precisely estimated, both figures show a very similar pattern of results. In panel (a), women in the 70th and 80th percentile of the exam score distribution still have on average a lower ratio of unique locations relative to unique specialties, although now the difference is only statistically significant at the 10 percent level. In panel (b), best performing women have on average a lower propensity to introduce in their list of preferences locations that are geographically distant to one another than men with the same choice set. There results suggest that even though women might not need to be as mobile as men, it does not explain the whole gender difference in spatial dispersion displayed in Figure 10.

Putting these results together suggests that women have a stronger preference for the location in which they work than their male counterparts. This is specially compelling for the results on geographic mobility, as our results corroborate previous findings in the literature.²⁶

²⁶See for instance [Le Barbanchon, Rathelot and Roulet \(2019\)](#) and [Fluchtmann et al. \(2020\)](#).

5.3 Preferences for Mobility of Married Women

Finally, we want to test whether being involved in a serious relationship affects one's preference for mobility. Given that we do not observe marital status for the entire sample, but only for women who have changed their name to their spouse's name, we focus on the sample of female candidates. We start by analysing whether the number of unique specialties and locations that are extracted by the algorithm during the simulation phase depends on marital status. Columns (1) and (2) in Table 2 support this hypothesis. When comparing non-married women to married ones, married women are found to input 9 percent fewer unique specialties and locations than non-married ones. Additionally controlling for choice set fixed effects results in married women having 22 percent fewer unique specialties and locations selected by the deferred acceptance algorithm on average. The considerable change in the coefficient after the introduction of choice set fixed effects reveals that married women are not uniformly distributed along the female performance distribution. Indeed, the proportion of married women decreases when going up the exam score distribution.

We then regress our proxy for preference for mobility on the indicator variable for being a married women at the time of choice. Column (3) shows that without controlling for choice set, the women which we identify as married have a 26 percent lower ratio than the women whom we identify as not married, on average. After controlling for choice set, the coefficient increases in magnitude to reach 43 percent. It suggests that married women are likely to favour location over occupation more than unmarried women. It is the case whether we control for choice set and unconstrainedness or not.

Finally, in columns (5) and (6) we estimate PPML models using our measure of spatial dispersion of the desired residency positions as the dependent variable. Our preferred specification shows incidence rate ratios for married women that are below 1, translating into married women introducing residency positions that are 39 and 54 percent less geographically dispersed than unmarried women with very similar choice set. We interpret this finding as married women putting substantially more importance than non-married women on being able to target a precise area of the country when deciding where to start their new job.

These three results are, to a certain extent, expected if we consider that married women are more likely to be more constrained in the location dimension than non-married ones. Nevertheless, our data allows to quantify by how much those potential constraints are affecting the mobility preferences of married women when choosing their occupation.

Table 2: Preferences for mobility of married women.

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Nb locations + specialties)		ln(Ratio locations to specialties)		Spatial dispersion (incidence rate ratios)	
Married	-0.09** (0.05)	-0.22*** (0.06)	-0.26*** (0.05)	-0.43*** (0.06)	0.61*** (0.11)	0.44*** (0.09)
Unconstrained	-0.34*** (0.02)		-0.30*** (0.02)		0.36*** (0.06)	
Observations	14,966	14,536	14,966	14,536	13,709	10,830
R-squared	0.02	0.35	0.01	0.34		
Choice set FE	No	Yes	No	Yes	No	Yes

Notes: This table shows the OLS, columns (1) to (4), and PPML, columns (5) and (6), estimates obtained from regressing three different measures of preferences for location and specialty on an indicator variable for being married and unconstrained in the residency choice for the population of women participating in the 2019-2021 residency selection process. In columns (1) and (2), the dependent variable is the natural logarithm of the sum of unique specialties and locations that the preference gathering algorithm obtained for each candidate during the simulation phase. In columns (3) and (4), it is the ratio of unique locations over the sum of unique locations and specialties. In columns (5) and (6) estimates are incidence rate ratios estimated by Poisson pseudo maximum likelihood of the spatial dispersion measure for each residency position in each candidate's proxy list of preferences. Year fixed effects are included in columns (1), (3) and (5). Choice set fixed effects defined as groups of 5 individuals with consecutive exam scores are included in columns (2), (4) and (6). Heteroskedastic robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Preferences for a Placement with a Partner

Another unique feature of the French residency selection procedure is that it allows candidates to choose their residency position together with a partner. We label the individuals who do so as *downgraders*. Even though this practice is not formally reserved for couples, we claim that candidates using it are likely to be. Indeed, doing so allows them to select residency positions satisfying a joint location target.

This feature offers the unique opportunity to study whether there exists a gender difference in the likelihood to give up on a better residency position in order to be able to work in the same place as one's partner. We do so on the subsample of couples which are identifiable through downgrading. To analyse whether there exist a gender gap in the probability of downgrading, we estimate equation (1) using an indicator for being a downgrader as the dependent variable. The information on downgrading is contained in the data we obtained from the CNG platform. Out of the 25,090 students who selected a residency position between 2019 and 2021, we find that 262 decided to downgrade, of which 143 were women. The share of women who downgrade is slightly smaller than the total share of women who participate in the NRE in that same period, 55 and 59 percent respectively.

Table 3 shows the gender gap in the probability to downgrade. Column (2), our preferred specification, shows that, compared to men, women are on average 0.26 percentage points less likely to give-up their turn for a later one during the official residency selection process. Compared to an average of only 1 percent of students deciding to downgrade, this corresponds to women being 26 percent less likely to downgrade their

Table 3: Gender gap in placement with a partner.

	(1)	(2)	(3)	(4)
	Downgrading		ln(Diff. ranks given-up)	
Female	-0.0021 (0.0013)	-0.0026* (0.0015)	0.058 (0.213)	0.112 (0.242)
Unconstrained	0.0017 (0.0042)	-0.0003 (0.0009)	0.414* (0.237)	0.334 (0.445)
Observations	25,090	25,089	262	257
R-squared	0.0003	0.1976	0.025	0.320
Choice set FE	No	Yes	No	Yes
Mean dependent var.	0.010	0.010		

Notes: This table shows the OLS estimates for the gender gap in the probability of downgrading (columns (1) and (2)) and the gender gap in the size of the gap that exists between the rank which is given up and the rank which is taken after downgrading (columns (3) and (4)). The dependent variable in columns (1) and (2) is an indicator variable for being a downgrader. The dependent variable in columns (3) and (4) is the natural logarithm of the difference between the initial rank and the new rank for those who downgraded. Year fixed effects included in columns (1) and (3). Choice set fixed effects defined as groups of 5 individuals with consecutive exam scores are included in column (2). Fixed effects for year by exam rank ventile are included in column (4). Heteroskedastic robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

rank to choose their residency position with a partner. The estimate however, is statistically significant only at the 10 percent level. Turning to the intensive margin of this behaviour, we then analyse whether there is a gender gap in the size of the gap that exists between the rank which is given up and the rank which is taken after downgrading. We thus regress the natural logarithm of this gap on the female dummy, and show the results in columns (3) and (4) of Table 3. The results do not allow us to reject the null hypothesis that male and female downgraders differ in the number of turns that they are willing to give up in order to select their residency position together with their partner.

7 Conclusion

In this paper, we analyse gender differences in early career choices in a context in which the traditional explanations for gender-based occupational segregation, namely human capital investment and discrimination, are by construction not present. It allows us to focus on the role of supply side factors in explaining gender-based occupational segregation.

Using unique data on the procedure used in France to allocate medical students to residency positions, we show that conditional on facing virtually equivalent choice sets, men and women make drastically different occupational choices. Moreover, we show that this result holds at the top of the performance distribution, where candidates do not face external constraints on their decisions, and where decisions thus reflect preferences. It suggests that preferences for occupational characteristics play an important

role in determining career choices. We investigate this further and show that women prefer to self-select into occupations which have lower expected earnings, allow for more time flexibility, are less competitive, and are more socially important than those in which men self-select.

We then turn to comparing men and women's occupation and location decisions when they face external constraints on their choices. As vacancies get filled, two types of trade-offs appear, the first between specialty and location, and the second between different specialty characteristics. In this paper, we focus on the occupation-location trade-off, and analyse whether men and women differ in their propensity to be mobile for their residency program. We find evidence suggesting that when the occupation-location trade-off appears, women are more likely to favour the location dimension than men. We further show that this behaviour is stronger for married women.

This paper can be extended in several ways. First, if we could observe not only the simulation allocation at each point in time, but also individual complete ordered list of preferences, we would be able to better identify actual individual preferences in terms of occupations and locations. Second, the analysis would be improved if we could reliably identify both married men and married women, as we believe that marital status is one of the most relevant elements to take into consideration when studying mobility decisions. Finally, another avenue for future research is to survey prospective NRE candidates to ask them about their preferences in terms of job characteristics and location and the reasons motivating these preferences, and then to compare these stated preferences to the realised allocation.

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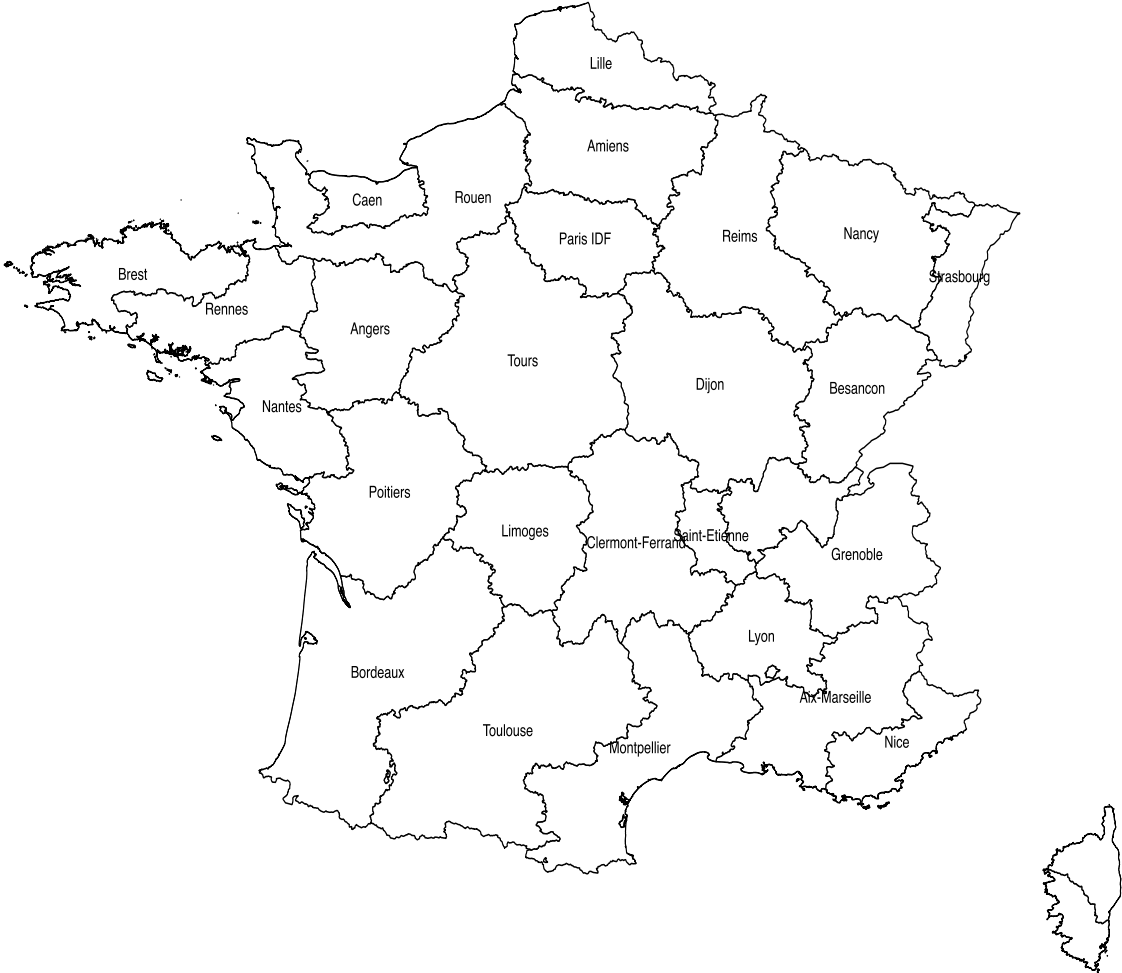
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Appendix

Appendix A Supplementary Material

Figure A1: Subdivisions



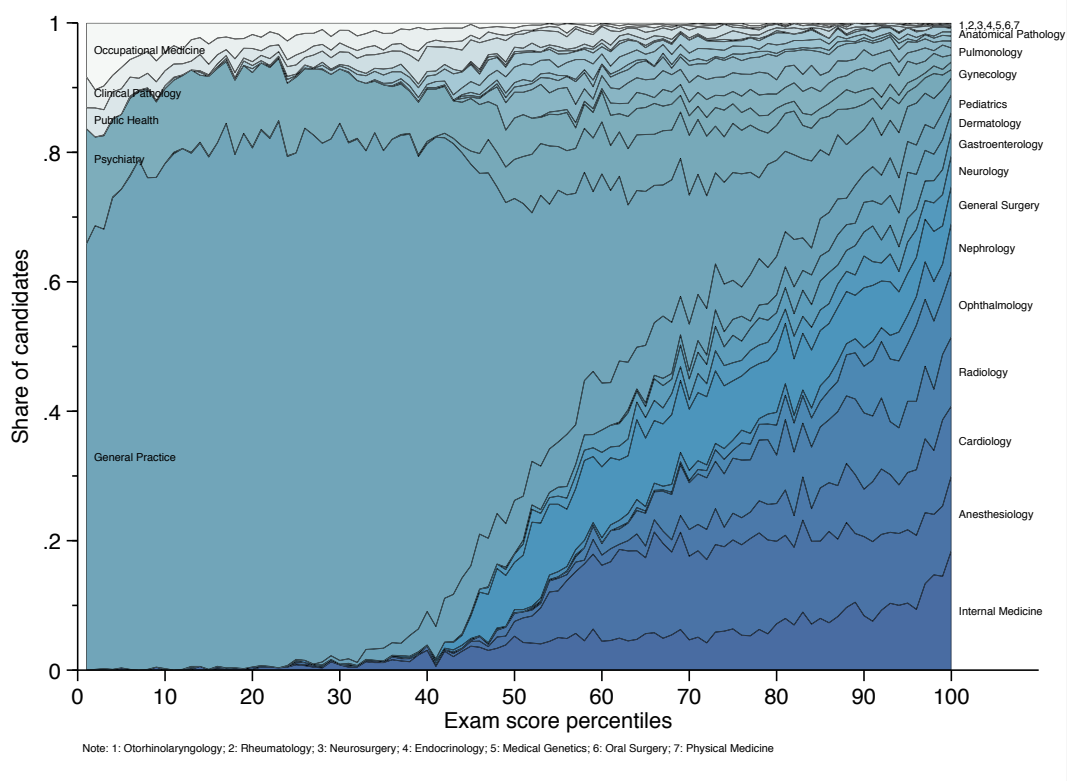
Notes: This figure shows the 26 subdivisions of continental France. Subdivisions are the geographical unit used at the NRE. There are two additional subdivisions in overseas France: Antilles-Guyane and Océan Indien.

Table A1: Selected specialty characteristics from O*NET.

Index	Measure	Question	Scale
Time pressure	Time pressure	“How often does your current job require you to meet strict deadlines?”	From never, to every day.
Competition	Competition	“How competitive is your current job?”	From not at all, to extremely.
	Concern for others	“How important is concern for others to the performance of your current job?”	From not at all, to extremely.
Social Contribution	Assisting and caring	“How important is assisting and caring for others to the performance of your current job?”	From not at all, to extremely.
	Social orientation	“How important is social orientation to the performance of your current job?”	From not at all, to extremely.
	Contact with others	“How much contact with others is required to perform your current job?”	From no contact, to constant contact.
	Work with a group or team	“How important are interactions that require you to work with or contribute to a work group or team to perform your current job?”	From not at all, to extremely.
Interactional Skills	Interpersonal relationships	“How important is establishing and maintaining interpersonal relationships to the performance of your current job?”	From not at all, to extremely.
	Social perceptiveness	“How important is social perceptiveness to the performance of your current job?”	From not at all, to extremely.

Notes: The O*NET database contains hundreds of standardised and occupation-specific characteristics on almost 1,000 occupations covering the entire U.S. economy. It is updated by ongoing surveys to workers sampled from each occupation’s worker population and occupation experts. From this database, we select the measures that we find relevant in this framework. All the measures are on a five-point scale. These measures are either taken as they are or aggregated into broader indices. We re-scale all our four indexes to have mean zero and a standard deviation of one, namely time pressure, competition, social contribution, and interactional skills.

Figure A2: Share of candidates selecting each specialty.



Notes: This figure plots the share of candidates selecting each specialty in each percentile of the exam score distribution.

Figure A3: Gender gap in self-selection into specialties across the exam rank distribution.

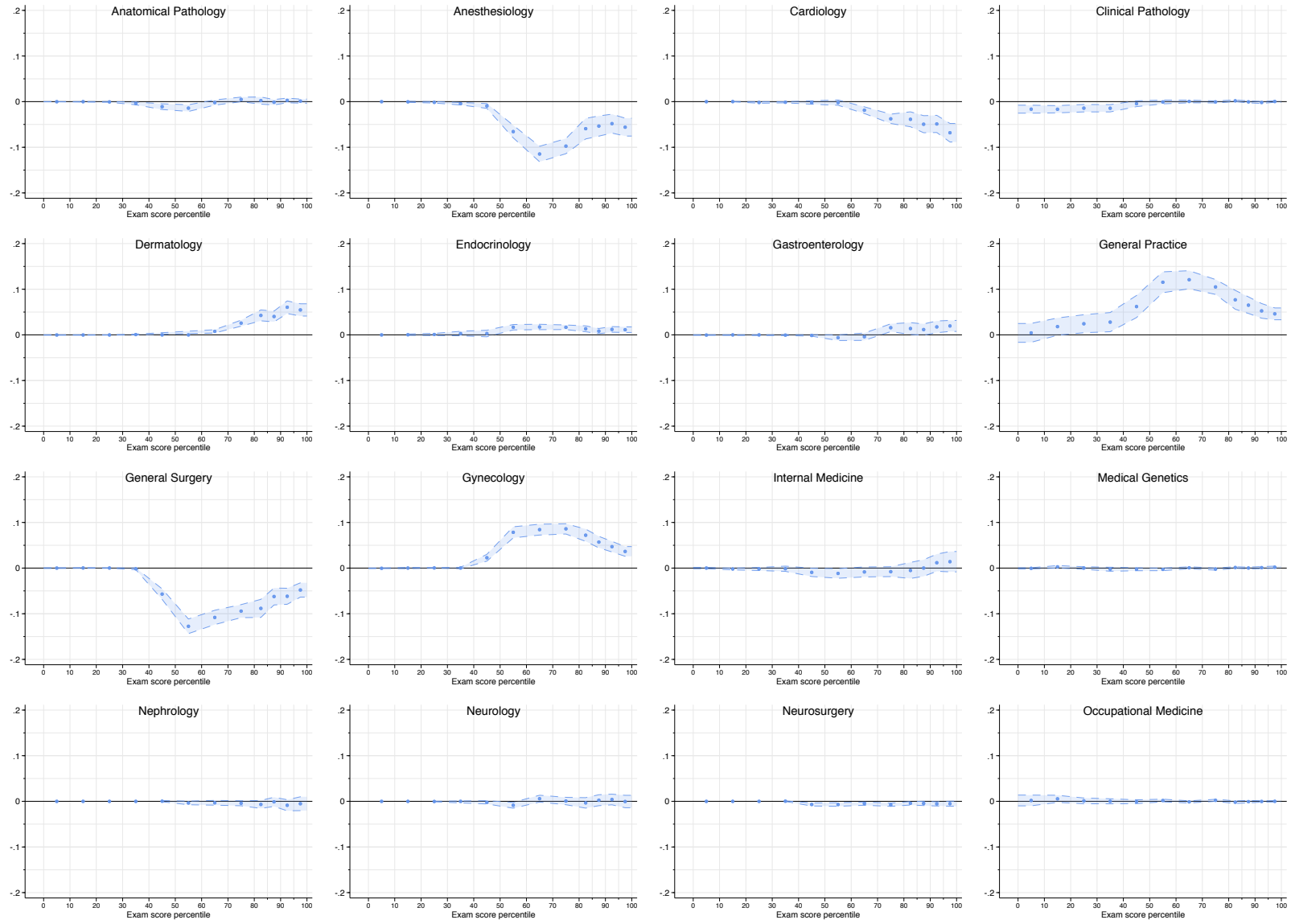
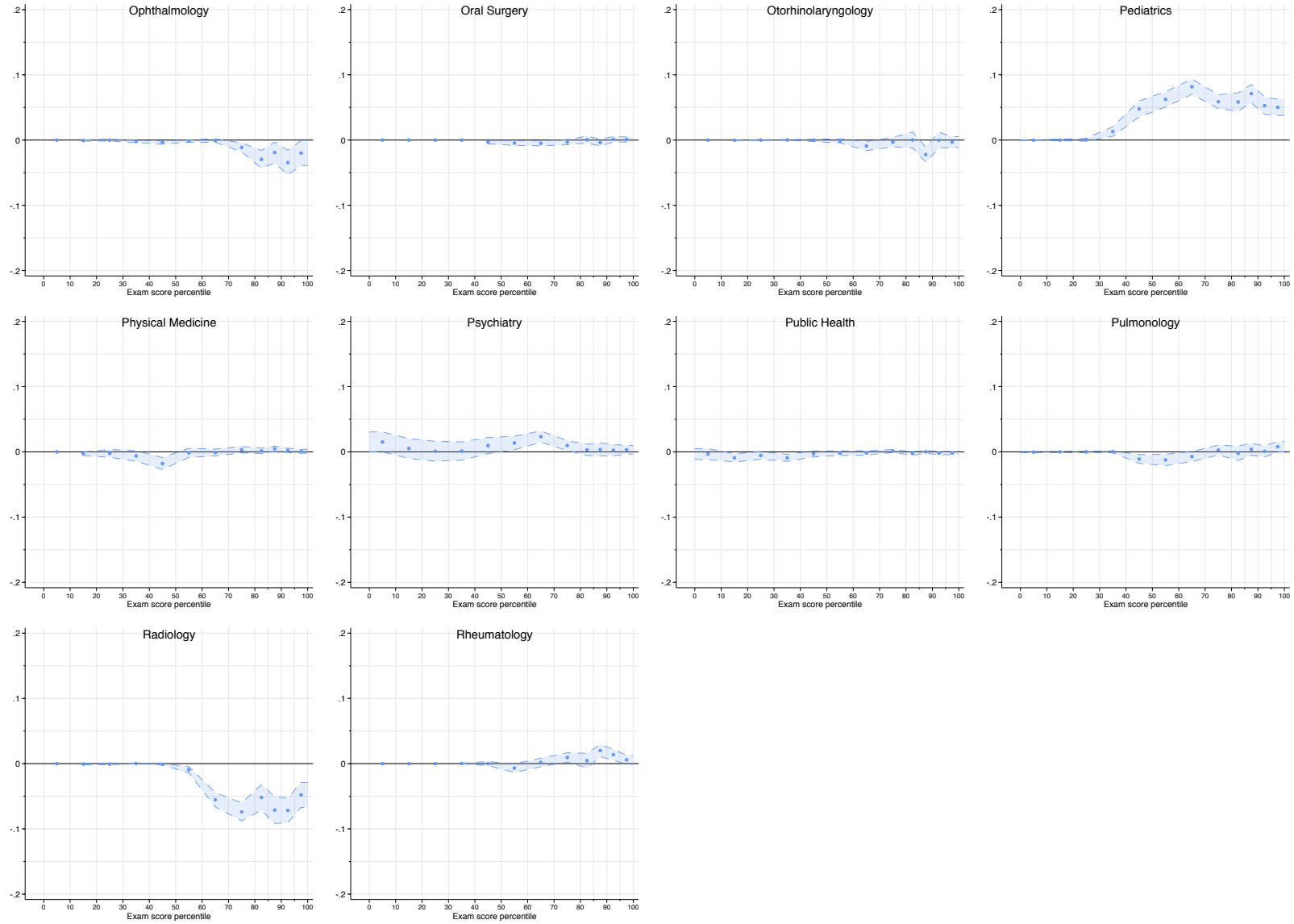
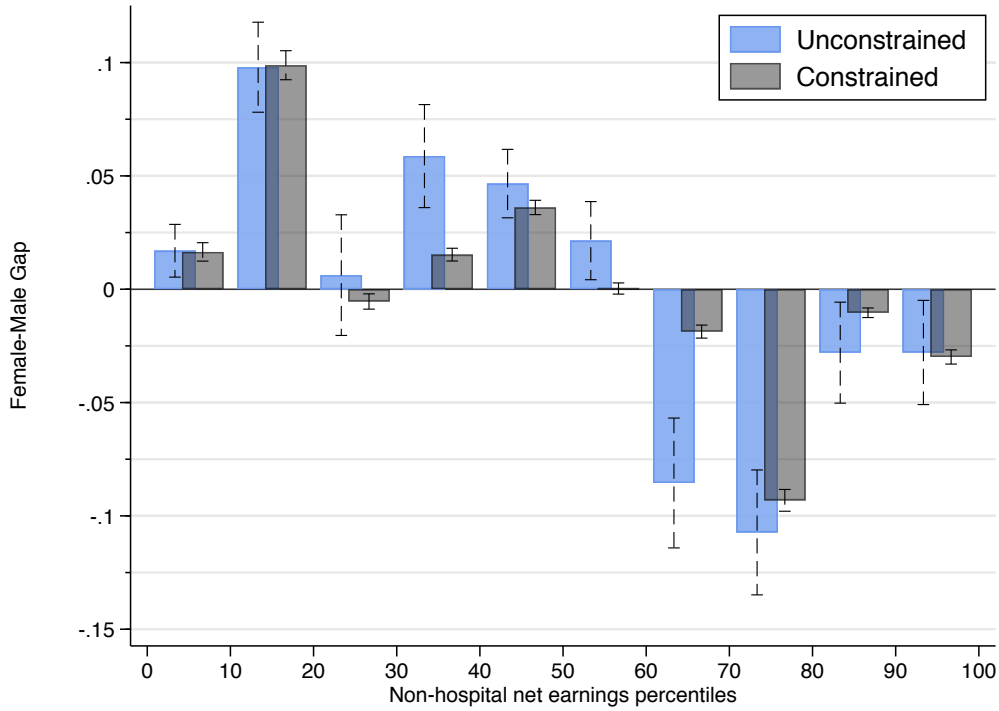


Figure A3 (cont.): Gender gap in self-selection into specialties across the exam rank distribution.



Notes: This figure plots the coefficients $\hat{\beta}$ and 95% confidence intervals in equation (1) estimated separately in each decile of the exam score distribution, for 26 medical specialties. Negative (positive) values indicate that on average females are less (more) likely to self-select into specialties with the corresponding attribute than males with a virtually identical choice set. All the gender gaps are estimated using OLS and include choice set fixed effects and include choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. The shaded area shows 95% confidence intervals using heteroskedastic robust standard errors.

Figure A4: Gender gap in selection on non-hospital earnings.



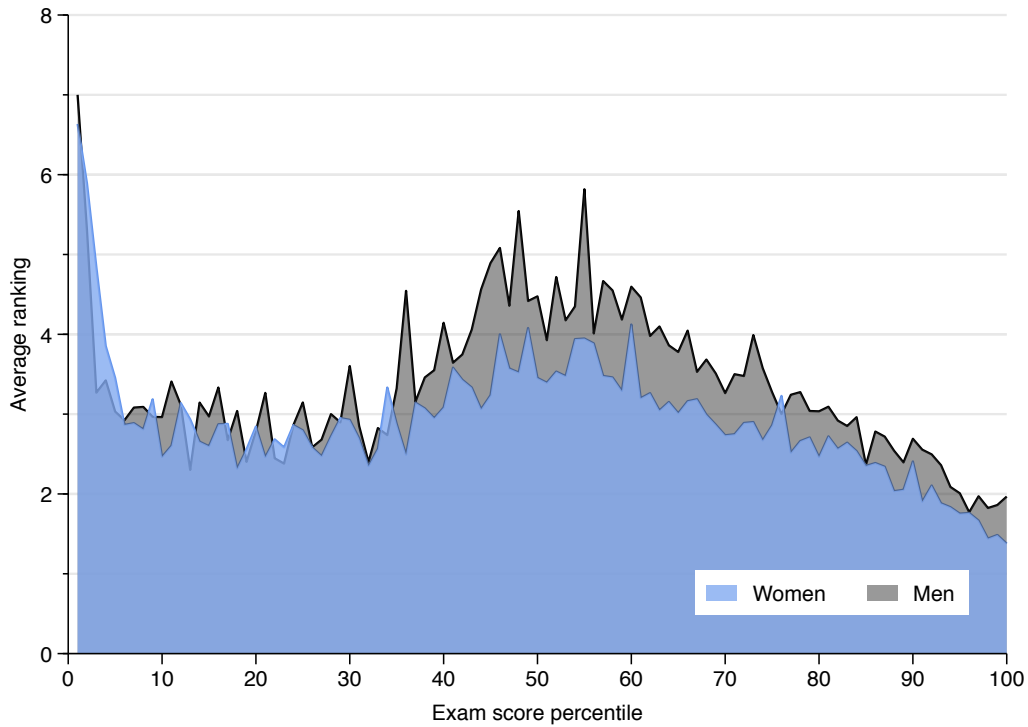
Notes: Gender gaps in the probability of females selecting a residency position that falls in each of the deciles of the non-hospital earnings distribution. Negative (positive) values indicate that on average females are less (more) likely to self-select into specialties with the corresponding attribute than males with a virtually identical choice set. The non-hospital earnings distribution is the average earnings earn by all doctors not working exclusively in a hospital in each region and specialty. Individuals choosing their specialty when 99% or more of the residency positions were still vacant are labeled as unconstrained, while the rest as constrained. All the gender gaps are estimated using OLS and include choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. Dashed vertical lines refer to 95% confidence intervals computed using heteroskedastic robust standard errors.

Table A2: Descriptive statistics on the 2019 to 2021 simulation phases.

	(1) Men	(2) Women	(3) Diff.	(4) p-value	(5) Obs.
Nb positions	3.305	2.961	0.344***	0.000	25,090
Nb specialties	1.740	1.600	0.141***	0.000	25,090
Nb subdivisions	2.675	2.443	0.232***	0.000	25,090
Rank of selected position on wish-list	3.305	2.961	0.344***	0.000	25,090
% downgraders	0.012	0.010	0.002*	0.093	25,090

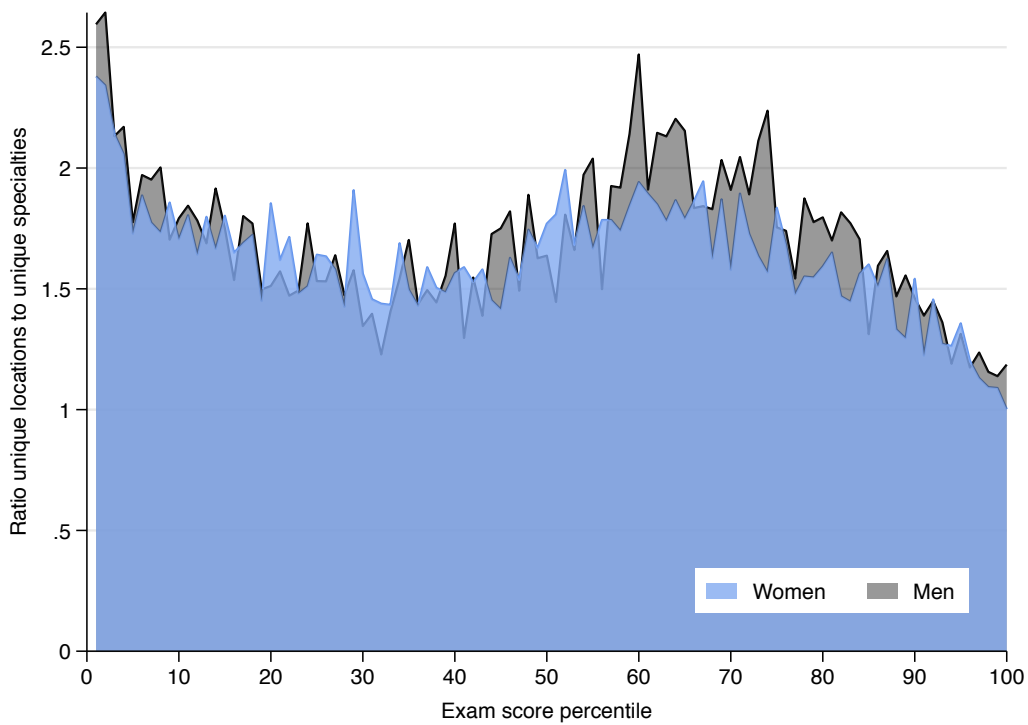
Notes: This table reports descriptive statistics for the simulation phases of the 2019 to 2021 NRE. Columns (1) and (2) report averages for men and women, respectively. Column (3) shows the difference between the men and women averages, and column (4) reports the p-values associated with the two-sample t-tests for the difference in means between men and women. Column (5) reports the number of observations.

Figure A5: Average rank of selected position in candidates' list of preferences.



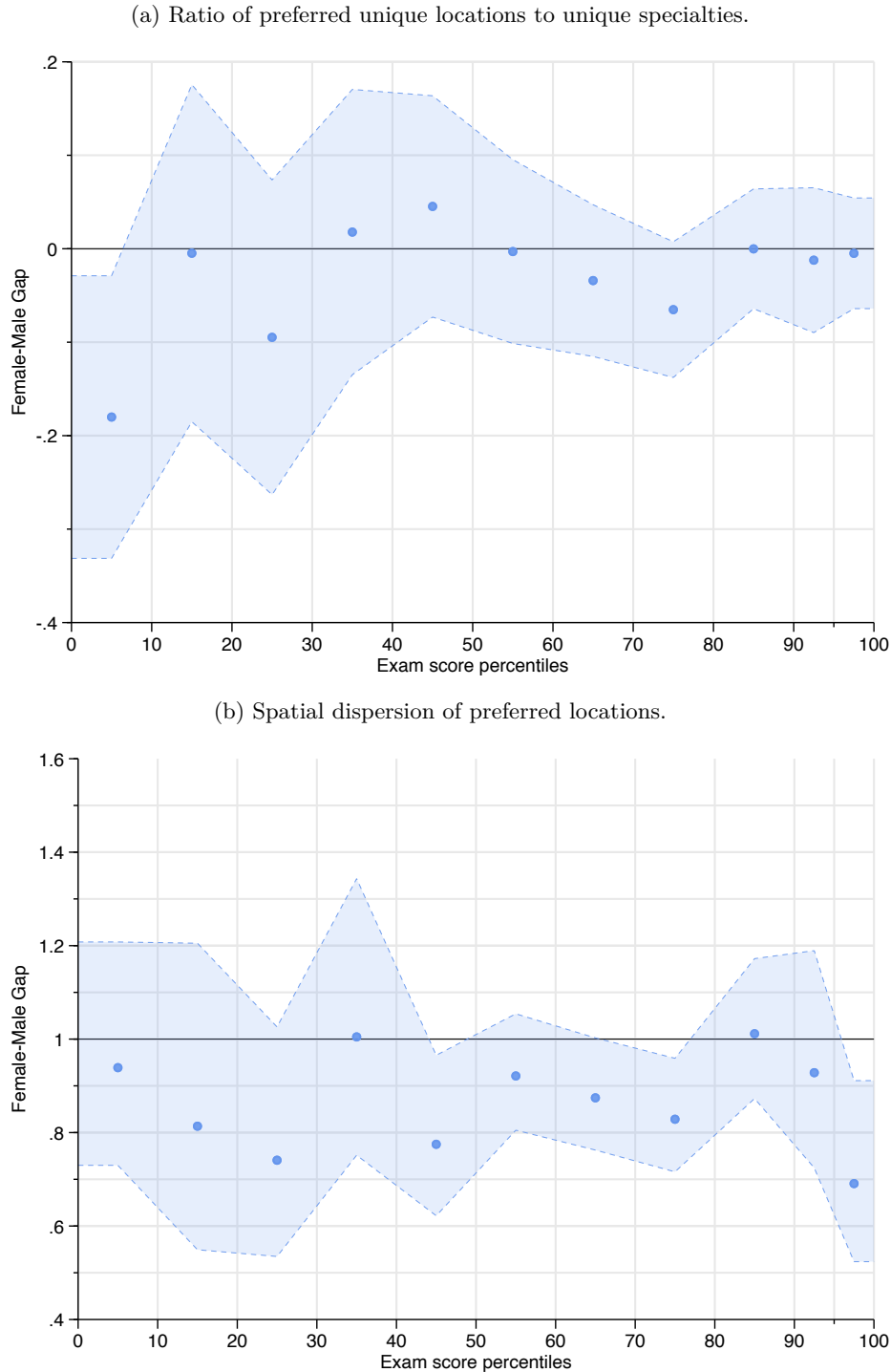
Notes: This figure plots the average ranking of the position selected in a candidate's list of preferences by the deferred acceptance algorithm during the simulation phase. They are plotted over the percentiles of the exam performance distribution, for men and women separately.

Figure A6: Average ratio of number of locations over number of specialties.



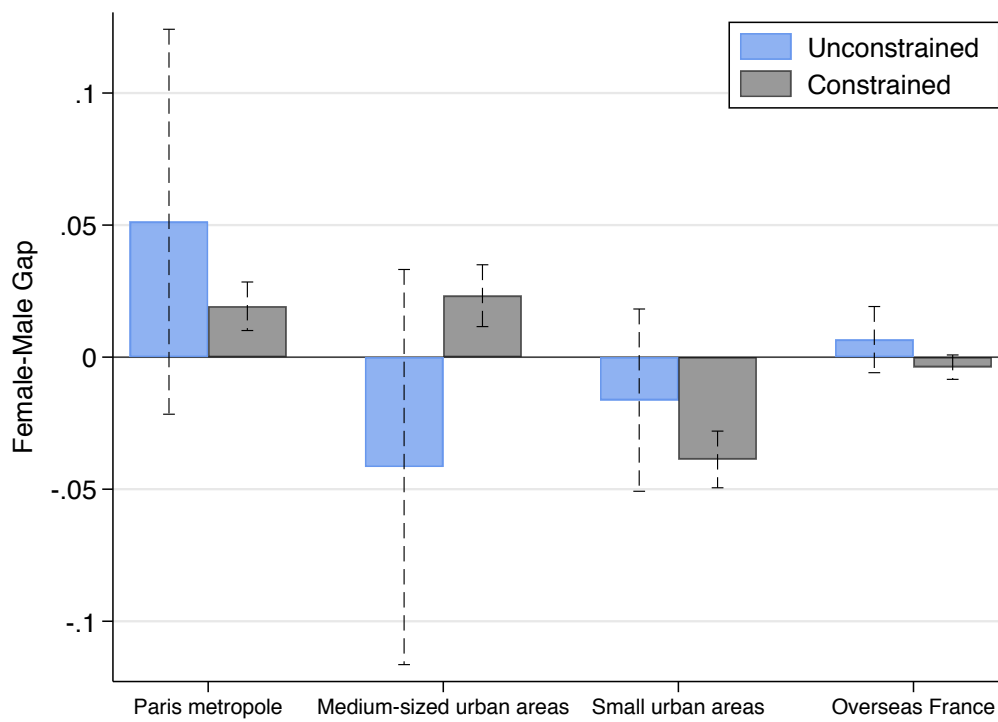
Notes: This figure plots the average ratio of number of unique locations over number of unique specialties selected in a candidate's list of preferences by the deferred acceptance algorithm during the simulation phase. It is plotted over the percentiles of the exam performance distribution, for men and women separately.

Figure A7: Gender gap in preferences for location, excluding general practice.



Notes: Panel (a) plots gender differences in the natural logarithm of the ratio of students' number of preferred locations over each student's sum of numbers of unique locations and unique specialties extracted by the deferred acceptance algorithm during the simulation phase excluding all the individuals for which General Practice is observed. Negative (positive) values indicate that on average a lower (higher) ratio is observed for women than for men with virtually equivalent choice sets. Panel (b) plots the estimated incidence rate ratio comparing women to men in terms of spatial dispersion of their preferred unique locations extracted by the deferred acceptance algorithm during the simulation phase excluding all the individuals for which General Practice is observed. Estimates are produced by estimating equation (1) using Poisson pseudo maximum likelihood and a measure of spatial dispersion as the dependent variable. Values below (above) one indicate that on average a lower (higher) spatial dispersion of desired locations is observed for women than for men with virtually equivalent choice sets. All the gender gaps are conditional on choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. The shaded area shows 95% confidence intervals computed using heteroskedastic robust standard errors.

Figure A8: Gender gap in preferences for location type.



Notes: This figure plots gender gaps in preferences for different location types, using data from the deferred acceptance algorithm, separately for the unconstrained and constrained groups. Negative (positive) values indicate that a lower (higher) ratio is observed for women than for men with virtually equivalent choice sets. Individuals choosing their specialty when 99% or more of the residency positions were still vacant are labeled as unconstrained, while the rest are labeled as constrained. All the gender gaps are estimated using OLS and include choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. Dashed vertical lines show 95% confidence intervals computed using heteroskedastic robust standard errors.

Appendix B Robustness Checks

In this section, we perform a series of sensitivity tests to assess the robustness of our results. First, we show that our baseline results are robust to an alternative definition of groups within which choice sets are considered as identical. Second, we show that the result according to which men and women who are unconstrained in their choices differ in their occupational choices is robust to alternative definitions of unconstrainedness.

B.1 Alternative Definition of Groups with Similar Choice Sets

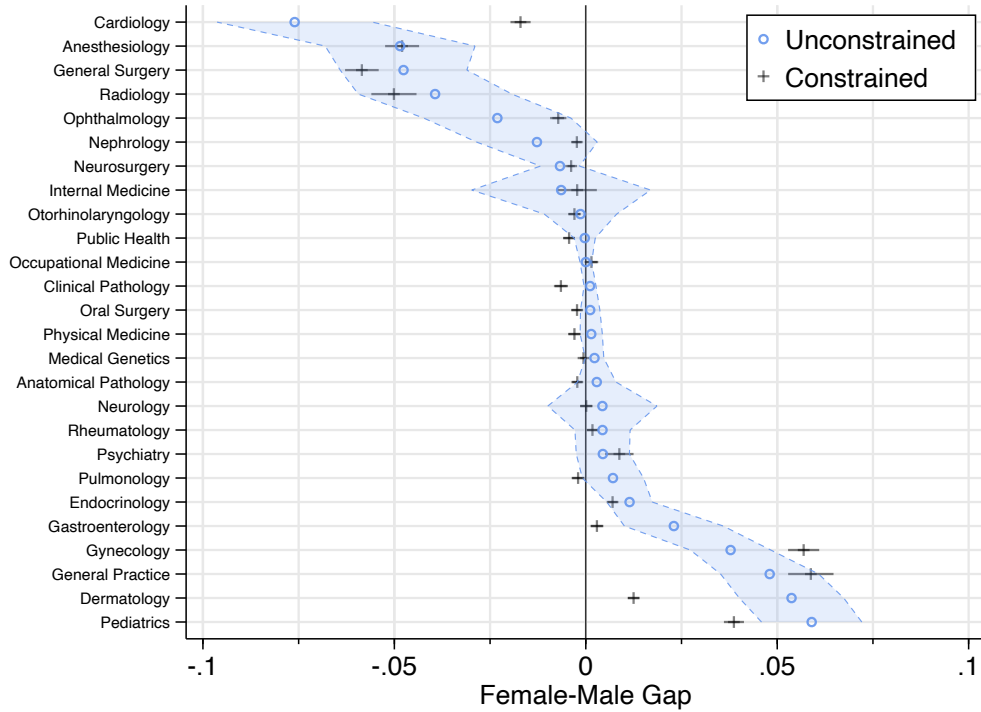
So far, we have considered the choice sets of five individuals with consecutive ranks as similar. Within such groups, the choice set of the best ranked and the worst ranked can at most differ by 4 positions. We now use two alternative, more restrictive definitions of these groups: (i) groups of individual facing exactly the same choice sets, and (ii) pairs composed of a man and a woman of consecutive rank. Using these definitions, we re-run the baseline analysis described in equation (1). The results are shown in Figure B1, and comparing them to those displayed in Figure 4 shows that our definition of choice set fixed effects is not driving our results.

B.2 Alternative Definitions of Unconstrainedness

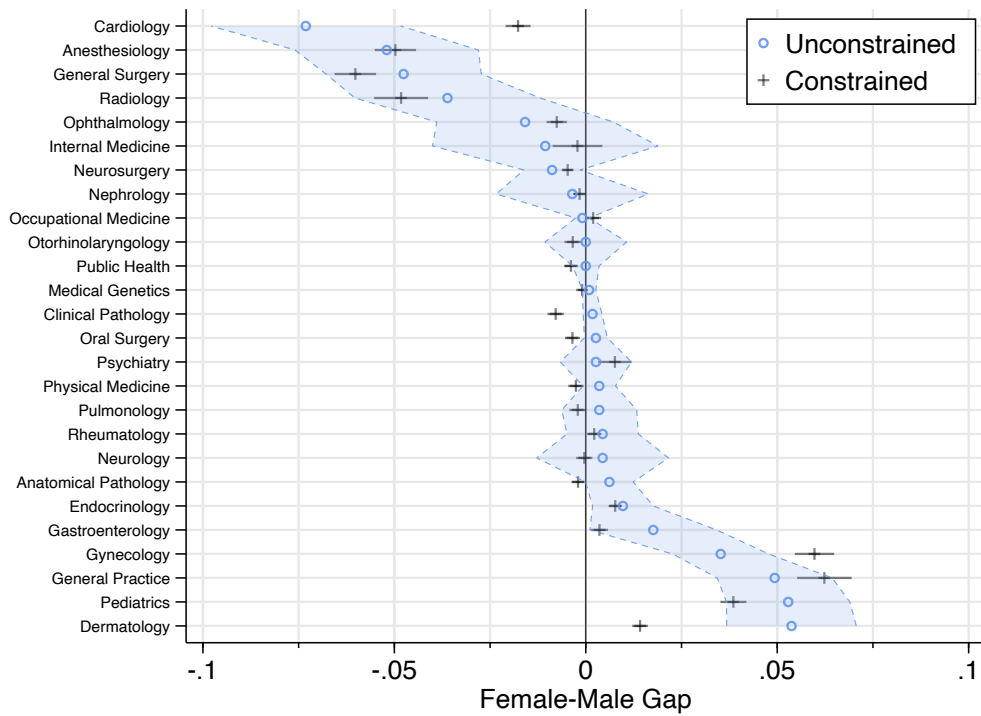
Unconstrainedness is the fact of making the occupational decision while facing no formal barriers to entry into one's preferred position. As a result, unconstrained job seekers are those who pick their job while 100 percent of positions are still available. Given that this definition is restrictive in terms of number of observations and thus largely decreases the statistical power of our analysis, we have instead decided throughout the paper to use as the unconstrained sample the group of job seekers who make their occupational choice when 99 percent of all positions are still available. In this section, we show that this choice does not drive our results, by replicating Figure 4 using the following alternative definitions of unconstrainedness: (i) making a decision while 100 percent of the positions are still available (*strict* unconstrainedness); (ii) making a decision while 99.5 percent of the positions are still available; (iii) belonging to the group of top 5 percent performers at the NRE. The results are displayed in Figure B2. Even though the results are qualitatively slightly different, the main result according to which men and women who are unconstrained differ in their occupational choices is largely unchanged.

Figure B1: Gender differences in self-selection into specialties, using an alternative definition of choice set fixed effects.

(a) Groups with strictly identical choice sets.



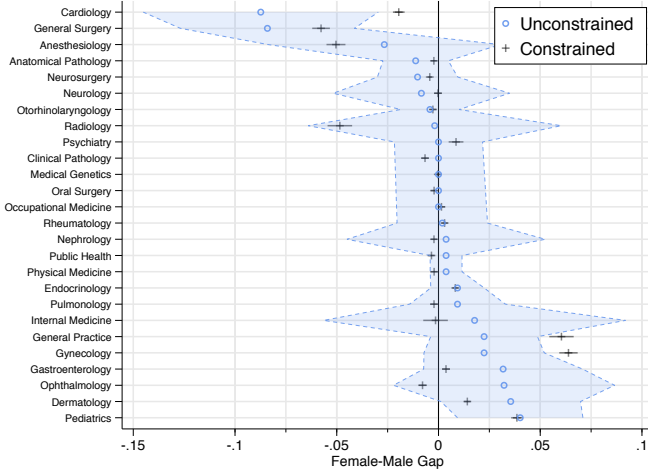
(b) Pairs of one man and one woman of consecutive exam scores.



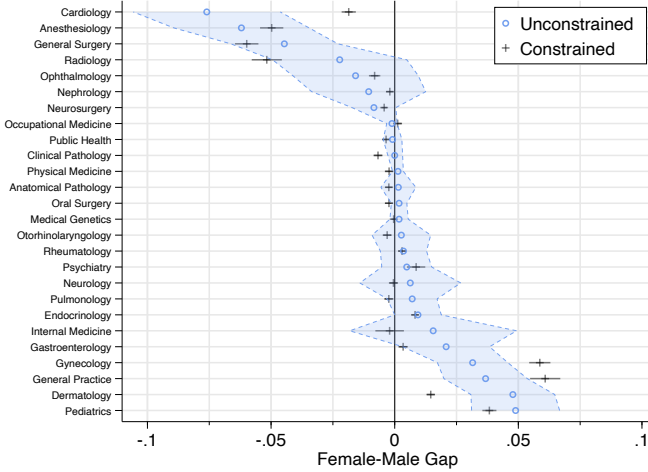
Notes: This figure plots the OLS estimates for the coefficients $\hat{\beta}$ and 95% confidence intervals estimated from equation (1) separately by specialty, using (a) groups with strictly identical choice sets, and (b) pairs of one man and one woman of consecutive exam scores as alternative definitions for choice set fixed effects. The shaded area (unconstrained sample) and horizontal solid black lines (constrained sample) show 95% confidence intervals using heteroskedastic robust standard errors.

Figure B2: Gender differences in self-selection into specialties, using alternative definitions of unconstrainedness.

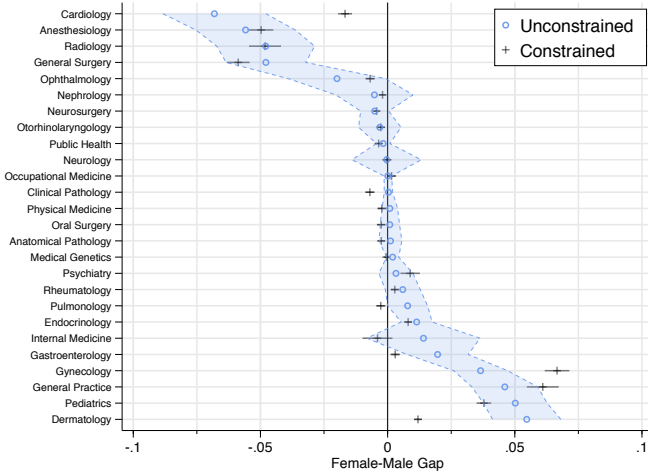
(a) 100% of positions are available.



(b) 99.5% of positions are available.



(c) Candidates in the top 5% of the performance distribution.



Notes: This figure plots the OLS estimates for the coefficients $\hat{\beta}$ and 95% confidence intervals estimated from equation (1) separately by specialty, focusing on (a) candidates who make their choice when all positions are still available, (b) candidates who make their choice when 99.5 percent of positions are still available, and (c) candidates belonging to the top 5 percent of the performance distribution. All regressions are estimated by OLS and include choice set fixed effects defined as groups of 5 individuals with consecutive exam scores. The shaded area (unconstrained sample) and horizontal solid black lines (constrained sample) show 95% confidence intervals using heteroskedastic robust standard errors.

Appendix C The Simulation Phase

After taking the National Ranking Examinations, and being assigned a rank based of their performance at the exam, students are prompted to take part in a simulation period organised by the CNG on a platform called CELINE. Candidates receive personal credentials which allow them to log into their CELINE account, and are asked to submit an ordered list of preferences.

Figure C1 provides an overview of what candidates see during this simulation phase.²⁷ After logging into one’s account, one must select a location (‘Subdivision’) and a specialty (‘Discipline/Spécialité’) as well as the rank that the position should have on the wish list (Box ①). After clicking on Submit (‘Ajouter un vœu’), the position is added to the list, which the candidate sees on the same page, below Box ①. After inputting one or several positions into the system, the candidate sees in Box ② his rank in the race to get a given position, as well as the number of vacancies available for that position. In the example below, the candidate’s first choice—Ophthalmology in Lille, that is the position which has rank 1 in Box ④— has 9 vacancies to offer, and all of them are taken by candidates who obtained a better rank at the NRE (‘épuisé’). As a result, the candidate’s second choice—Pediatrics in Lyon, ranked 2 in Box ④— is automatically selected by the allocation mechanism, given that only 12 better ranked candidates have been assigned to that position, for which there are 16 vacancies in total (Box ③).

Our data contains, at each point in time during the simulation phase, the list of all the automatically selected positions. In other words, it provides, at each point in time between the publication of the NRE ranking and the allocation days, a simulated allocation of candidates to positions.

Figure C1: Simulation phase example.

The screenshot shows the CELINE simulation phase interface. At the top, there are navigation buttons: 'rafraîchir', 'mes changements passés', 'mon activité passée', 'mon historique', and 'je me déconnecte'. Below these is a form to add a wish, with fields for 'en n° 1', 'Subdivision ...', and 'Discipline/Spécialité ...', and a button 'Ajouter un vœu'. The main part of the interface is a table of selected positions. The table has columns for rank, status, location, specialty, and a 'supprimer' button. The table is titled 'étudiants non CESP (ni ESSA) validés au-dessus de moi ont fait au moins 1 vœu' and 'en 13 / 16 le vœu n° 2 à LYON en Discipline : PÉDIATRIE permettra d'être affecté'. The table contains 7 rows of data.

Rank	Status	Location	Specialty	Action
1	épuisé / 9	LILLE	Spécialité chirurgicale : Ophtalmologie	supprimer
2	13 / 16	LYON	Discipline : PÉDIATRIE	supprimer
3	9 / 104	RENNES	Discipline : MÉDECINE générale	supprimer
4	9 / 227	LILLE	Discipline : MÉDECINE générale	supprimer
5	11 / 31	LILLE	Spécialité chirurgicale : Chirurgie générale	supprimer
6	1 / 4	ANTILLES-GUYANE	Discipline : PÉDIATRIE	supprimer
7	18 / 66	ILE DE FRANCE	Discipline : PÉDIATRIE	supprimer

Notes: This figure shows a candidate’s wish-list at a given point in time during the NRE simulation phase on the CELINE platform (<https://www.cngsante.fr/chiron/celine/>).

²⁷Note that the rank of the candidate appears on the page in place of the orange rectangle, but that we removed it for anonymity reasons.