EUI DEPARTMENT OF ECONOMICS

Essays in Empirical Microeconomics

Josep Amer Mestre

Thesis submitted for assessment with a view to
obtaining the degree of Doctor of Economics
of the European University Institute

Florence, 19 December 2022

European University Institute
Department of Economics

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Abstract

This thesis is composed of three independent chapters in applied microeconomics.

The first chapter studies the effect of interest groups on legislative voting. Using the alphabetic allocation of seats in the European Parliament, we show that former employees of interest groups influence the voting behavior of their colleagues when sitting together. When the subject of the vote is relevant to the interest group, the probability that nearby colleagues cast the same ballot increases by 2.4 percent, and that of abstention decreases by 9 percent, while no effect is detected for other vote subjects. These probabilities increase for votes about budgetary allocations, being comparable to those of sitting beside motion leaders. Revolving doors are problematic for the political process also when working in reverse.

The second chapter studies gender differences in early occupational choices: 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 us 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 choice set 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.

The third chapter studies the causal effects of welfare benefits supporting parents with low birth weight newborns on their subsequent fertility and the mother's labor market decision. I exploit the discontinuities in the eligibility criteria that entitles parents of newborns with birth weights below certain thresholds to receive monetary payments to devote themselves to the care of their newborn child, fully funded social security contributions and information courses. Using Spanish birth register data, I find that these welfare benefits impacted both the extensive and intensive margin of the fertility decision of low

socioeconomic households. Mothers in these households who have a newborn with a birth weight right below 1100 grams are on average 6 percentage points (19 percent) more likely to have a subsequent child compared to similar mothers with newborns right above that threshold. This effect is mostly coming from young mothers for whom the benefits are also found to substantially reduce the time to have the subsequent child. These mothers are also found to be 16 percentage points (27 percent) more likely to hold a job at the time of their subsequent birth. These effects are presumably coming through the increase in available resources that low socioeconomic status households can dedicate towards the care of their extremely low birth weight newborns.

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Two of the chapters in this thesis have been written with co-authors, to whom I owe special thanks, Miguel Alquézar-Yus and Agnès Charpin. I feel extremely indebted to their immense contributions to the quality of this thesis and for the innumerable conversations we shared, which undoubtedly added to the joy of writing it.

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Last but not least, my most special thank you goes to my brother and my parents, for their unconditional love and efforts in granting me the opportunity to make this possible. Finally, I wish to thank the person who is always on my side, Esther, for her unwavering love, encouragement, and faith in me. I dedicate this thesis to all of you.

Contents

Chapter 1

Reverse Revolving Doors: The Influence of Interest Groups on Legislative Voting

joint with Miguel Alquézar-Yus[1]

1.1 Introduction

Lobbying directed to European Union institutions by special interest groups has become a key issue in the EU decision-making process. As of 2018, there were more than 12.000 organizations registered as representing particular interests at the EU-level policy making, spending a total of €2.38 billion on lobbying-related activities. This constitutes the second largest lobbying industry in the world, only after the US.[2] Interest groups engage in multiple activities to directly persuade legislators of their position, such as drafting reports with arguments in favor or against specific motions and conducting meetings with lawmakers, with the main goal of instructing them on how to vote on specific motions.

Members of the European Parliament (MEPs), surveyed by Hix et al. (2016), report receiving a weekly average of at least 21 meeting requests from interest groups, to which

[1]We are indebted to our advisors Michèle Belot, Andrea Ichino and Sule Alan for their continued encouragement and guidance. We wish to thank Thomas Crossley, Alessandro Ferrari, Simon Hix, David Levine, Andrea Mattozzi, Alessandro Saia, Stefan Thierse and Zheng Wang and seminar participants at the 2020 European Consortium for Political Research general conference, Bavarian Young Economists' Meeting 2021, Queen Mary University of London, Universitat Autònoma de Barcelona, 28th Meeting on Public Economics, SIOE 2021 conference, 15th CESifo Workshop on Political Economy, PhD-EVS 2021, and at the EUI Microeconometrics Working group for helpful comments. Financial support from the Salvador Madariaga-EUI scholarship is gratefully acknowledged by both authors. All errors remain our own.

[2]According to OpenSecrets.org, in 2018, the US federal lobbying sector accounted for 11.600 organizations spending $3.42 billion. The listed EU figure was computed using the lobbying budget reported by the interest groups in the European Transparency Register.

59 percent of them admit attending at least once a week. Moreover, 89 percent of the interviewed MEPs report receiving voting instructions directly from interest groups on specific motions.

A subtler practice that is also available to interest groups is to rely on the so-called *reverse revolving doors*. This practice refers to the flow of individuals who were formerly employed by interest groups and subsequently became active in politics. Reverse revolving doors may be considered a subtle form of lobbying since allows interest groups to potentially place industry insiders with a hidden private agenda in democratically elected institutions. Indeed, 22 percent of the surveyed MEPs admitted having been encouraged to stand as a member of the European Parliament by an interest group representative.[3]

In this paper we investigate to what extent the voting behavior of the members of the European Parliament is affected by the presence of fellow legislators who worked for an interest group before being elected into office. To identify all legislators formerly employed by interest groups, we match their résumés – which they submit upon taking office – with the list of organizations registered as exhibiting interest in the European Union policy making, known as the *Transparency Register*. We find that 28 percent of the MEPs elected between 2004 and 2019 worked for an organization listed as an interest group at some point before taking office. The positions found range from short working spells on regional NGOs to high-level consulting jobs in lobbying firms.

The main empirical challenge to estimating the causal effect of reverse revolving doors on the legislative process is to obtain a relevant metric of connection between legislators that is also exogenous to the characteristics predicting their voting behavior. We address this issue by using the seating adjacency of legislators in the European Parliament, in which non-leader members of the main political groups sit in alphabetic order. First, the existence of such a norm is primal for our study, given that lawmakers who sit next to each other during plenary sessions are more likely to interact and are found to influence each other's views (Masket, 2008; Saia, 2018; Harmon, Fisman and Kamenica, 2019; Lowe and Jo, 2021). Second, the links between members, fostered by the alphabetic seating rule, can be regarded as being as good as random after conditioning on specific observable characteristics (Harmon, Fisman and Kamenica, 2019). Thus they allow us to obtain causal estimates on the influence wielded by MEPs with interest group background on their colleagues' voting behavior.

To provide clear evidence on the role of interest groups in legislative voting through the practice of reverse revolving doors, we follow a twofold approach. First, we build a novel dataset linking the employment histories of MEPs – identifying those who worked in an

[3]The Executive Order 13490, enacted during the first day of Barack Obama's presidency, banned the appointment of lobbyists into any executive agency they had lobbied for a period of two years. Despite this directive, as of 2017, 148 former lobbyists had been appointed into various executive agencies of the Trump administration (OpenSecrets.org accessed 11 October 2021).

interest group – with all their cast ballots, seating positions and roles in Parliament. This allows us to control for an exhaustive set of observable characteristics regarding the MEPs whose voting behavior we are interested in, as well as for those of their seating neighbors. These controls, which include measures of their previous professional experience, the legislators' fields of expertise, and their past roles in Parliament, minimize pre-existing relevant differences among our two types of MEPs, i.e., those with working experience in an interest group and those without. This comprehensive set of controls helps us isolate the influence that the MEPs with prior interest group experience exert on their peers' voting behavior from the most common potential confounders.

Second, we further enrich our dataset by linking the economic activity of the interest groups that employed MEPs with the subjects of each motion that was voted on in the European Parliament at any point during our studied period. The legislation enacted in the European Parliament covers a wide range of subjects, ranging from policies affecting agriculture, transport, and other crucial industries, to regulations on consumers' protection and the Union's single market. For instance, we link all the motions on energy policy to those interest groups we detected in the legislators' résumés which operate in the energy sector; all the legislation related to capital markets to interest groups operating in the financial sector, and so on.[4] Identifying which legislation is relevant for the interest groups in our sample is a crucial step in the process of evaluating the impact that reverse revolving doors can have on the lawmaking process. Specifically, it allows us to disentangle the effects emanating from a legislator being influenced by colleagues who used to work for interest groups in two very different situations: when the interest groups' economic activity is related to the motion being voted on and when it is not.

Our procedure allows us to distinguish between two potential factors affecting the voting behavior of MEPs who might be subject to the consequences of reverse revolving doors' activity. First, it allows us to estimate the average causal effect on the compliers of seating next to colleagues formerly employed by interest groups. Second, it allows us to obtain the additional causal effect of seating adjacent to such type of legislators whenever the subject of the motion being voted on is related to their interest groups' economic activity. Thus we can disentangle the effect emanating from a legislator being influenced by a colleague who used to work for an interest group whose economic activity is unrelated to the motion being voted on, from the same effect when the outcome of the vote may affect the interest group's economic activity. Under our working assumption that former interest group employees will lean towards legislation that is more favorable to their past employers, our research hypothesis is that this type of MEPs will only affect

[4] An example of a piece of legislation that we find to be relevant to the interest groups operating in the energy sector is the 2010 regulation on state aid to facilitate the closure of noncompetitive coal mines. Similarly, an important regulation for those interest groups operating in the financial sector is a 2010 directive on supplementary supervision of financial entities.

how their seating neighbors vote when the votes are considered to be of relevance to their past employers.

We find that legislators whose seating neighbor used to work for an interest group are 2.4 percent more likely to coincide in their ballots when the voting motions are related to the interest group's economic activity, compared to those sitting beside a legislator with no experience in an interest group. The magnitude of such effect corresponds to 57 percent of the influence exerted by those party members in charge of drafting the motions voted upon – known as shadow rapporteurs – or 43 percent of the magnitude of sitting next to colleagues from the same national party. In contrast, we find no statistically significant effect of sitting next to a former interest group employee when the vote is not related to the interest group's economic activity.

The influence that former interest group members exert on their colleagues is found to be extremely important in high-stake votes. Legislators sitting beside former interest group employees are 5 percent more likely to cast the same ballot in motions containing large public expenditure decisions, such as those on the European Union budget. The main effect of reverse revolving doors is found to be driven by national interest groups, as opposed to those based in the de facto capital of the European Union, Brussels. No differential influence is found along the interest group's business nature – namely, whether it is a for-profit or a not-for-profit organization.

Not all MEPs are affected in the same way by their colleagues' past professional experience in an interest group. We find that female MEPs and first-time elected members are the main groups driving the increase in the likelihood of casting the same ballot as their neighboring former interest group members during motions related to the groups' economic activity. In contrast, those legislators that are themselves former interest group members are not influenced by their neighboring colleagues who also worked for those type of organizations. Similarly, legislators with interest group background do not influence their peers' voting behavior when those are experts on the motion at stake. These results suggest that former interest group members provide biased advice, not achieving voting adherence among legislators with expertise or lobbying know-how.

Finally, we shed light on how the legislators' ballots are actually influenced by exploring their voting mobilization. We find that former interest group members influence their peers to reduce their abstention ballots when the motions are relevant for their former employers. Legislators with interest group background also increase their peers' presence in parliament for all types of motions. Further results suggest, however, that legislators slowly learn their seating neighbors' leanings and preferences, and accordingly start accounting for them by progressively reducing the number of ballots on which they agree.

To the best of our knowledge, this is the first study providing evidence of the distort-

ing effects generated by reverse revolving doors on the legislative process. These findings have important implications for policy making as they shed light on a relatively overlooked lobbying practice used by interest groups, consisting of having insiders sitting in democratically elected institutions. Our results support the hypothesis that revolving doors are problematic for the political process also when working in reverse.

This paper contributes to the literature by reconciling two long-standing areas of study within economics, one on voting behavior determinants and the other on the effects of lobbying on the decision-making process. First, our paper complements the literature on the determinants of legislators' voting behavior which goes back to Rice (1927) and Routt (1938).[5] Existing evidence on how legislators affect each other's voting behavior is still very limited. Cohen and Malloy (2014) and Battaglini, Sciabolazza and Patacchini (2020) identify congresspeople graduating from the same institution as being socially connected in order to study how their network's voting behavior affects their own individual voting behavior. Masket (2008) is the first one to use the seat of legislators as a determinant of their interactions and therefore potential voting influence on each other. He uses data from the Californian Assembly, from 1941 to 1975, to provide evidence that legislators sitting next to each other share a common voting history. Recent research has been devoted to approaching these peer effects among legislators from a causal perspective. Saia (2018) and Lowe and Jo (2021) use the Icelandic parliament random seating rule to examine voting and speeches' similarities. Using the European Parliament setting, Harmon, Fisman and Kamenica (2019) estimate how peer effects affect voting coincidence, as well as heterogeneous effects across various shared personal characteristics, such as sex and nationality, and for close margin votes. We contribute to this literature by focusing on how legislators' previous working experience in an interest group affects their seating peers' voting behavior.

Second, this work relates to the literature on lobbying in politics which harks back to Logan and Fellow (1929). Some recent studies have provided compelling evidence in favor of the argument that the lobbyists' main asset is their connection with policymakers. Blanes i Vidal, Draca and Fons-Rosen (2012) find that U.S. Senate ex-staffers experience a 24 percent drop in their lobbying revenue when the Senator they used to work for leaves office. Bertrand, Bombardini and Trebbi (2014) show that lobbying in the U.S. Congress is based on political connections rather than on industry expertise, as lobbyists tend to follow politicians to whom they are connected as they move across different policy areas. A blossoming literature using statistical models for network data has studied how legislation co-sponsorship is influenced by interest groups' campaign contributions

[5] A growing literature has covered in recent years how legislators' careers, prior to entering parliament, influence the working committee to which they are assigned (Adler and Lapinski, 1997; McElroy, 2006; Yordanova, 2009; Martin and Mickler, 2019), their leadership roles (Daniel and Thierse, 2018), and voting behavior (Francis, 2014; Van Geffen, 2016).

(Battaglini and Patacchini, 2018) and by legislators' connections with interest groups (Fischer et al., 2019).[6] Our paper is the first one to causally study how interest groups influence legislative voting. We do so by focusing on a commonly overlooked practice used by interest groups: the placement of industry insiders in democratically elected institutions.

The remainder of the paper is organized as follows: Section 1.2 explains the institutional setting. In Section 1.3 and 1.4, we present our data and describe it, respectively. Section 1.5 exposes the empirical strategy followed. Section 1.6 presents the main results, and Section 1.7 concludes.

1.2 Institutional Setting

1.2.1 Legislative voting in the European Parliament

The European Parliament is the lower legislative branch of the European Union. Members of the European Parliament (MEPs) are chosen through elections held in each EU member state. Once elected, they join cross-national European Political Groups (EPGs) based on their national party's ideology. EPGs comprise legislators from different nationalities but with like political affiliations. These groups operate and perform actions similar to those of conventional political parties in national parliaments. Prior to every vote, each group discusses their position internally; however, and crucially for our analysis, every MEP has always the right to unilaterally choose which ballot to cast in every single vote.

Each EPG's position is actively promoted through the appointment of *rapporteurs* and *shadow rapporteurs*. A rapporteur is the MEP in charge of drafting, and subsequently promoting during plenary sessions, a report on the legislative proposal at stake. Although, there is only one rapporteur per piece of legislation, the remaining groups can appoint their own shadow rapporteur to represent their political views in the proposal's drafting process.

We use the role of rapporteurs for two main purposes. First, given the wide variety of legislation voted upon at the European Parliament, ranging from non-binding opinions to far-reaching regulations, we use the appointment of rapporteurs as the means for distinguishing important motions from less prominent ones.[7] Hence, in our analysis we restrict our attention to those motions for which a rapporteur was appointed. Second, rapporteurs are entrusted by their parties to increase the Parliament's support for a specific motion,

[6] Further information on the lobbying literature can be found in De Figueiredo and Richter (2014) and Bombardini and Trebbi (2019).

[7] The selection of a rapporteur is done through a sophisticated auction, in which EPGs bid "points", awarded in relation to their relative size in the chamber. Motions with no rapporteur correspond to those votes where no bid was placed. For further information, see Ringe (2010) and Daniel (2015).

which requires influencing the vote of not only their party colleagues, but also of other groups' members. For this reason, we introduce a set of controls to account for the role and influence of rapporteurs and shadow rapporteurs on their colleagues. Table 1.14 in the Appendix displays how motions with rapporteur compare to those without. It provides evidence for the higher relative importance of motions with a rapporteur measured by the type of procedures being voted on, as virtually all Budget of the Union and the Ordinary procedures are led by a rapporteur. Moreover, motions with a rapporteur are characterized by a lower proportion of non-binding parliamentary own resolutions and a lower absence rate.

The European Parliament meets once or twice a month, during the so-called plenary sessions, in one of its two venues, located in Brussels and in Strasbourg. These plenary sessions represent the final step of the legislative process, in which legislation is debated and voted on.[8] There are three different ways in which MEPs can cast their ballot, namely by show of hands, by secret ballot, or by electronic vote.[9] In our analysis, we work with electronic votes, which represent around 2/5 of the total votes submitted during the studied period, as they identify the ballot cast by each individual MEP. To cast a vote, legislators need to first obtain recognition in the system by inserting their unique ID card in their own voting device, and subsequently press the button with their preferred choice. Casting a ballot for a colleague is strictly forbidden and penalized by the Parliament's norms.

1.2.2 Alphabetical seating in the chamber

The seating arrangement in the European Parliament's chambers is regulated by the rules of the Conference of Presidents. MEPs belonging to the different European political groups are clustered together in the chamber, and groups are allocated from left to right according to their political orientation. Figure 1.1 shows the seat distribution at the Strasbourg's venue, highlighting the block seating allocation by the European political groups. Within these groups, leaders sit in the front rows while the remaining seats are generally allocated in alphabetical order by surname. The five largest groups, namely S&D, Verts/ALE, ALDE, PPE, and ECR, adhere to this seating rule.[10] In total, 55.7% of

[8]The average plenary session convenes legislators for 4 days. These voting dates start at 9 a.m. and last till 10 p.m. During that time, MEPs are expected to sit in their allocated seat, only being allowed to move around the hemicycle in between debates.

[9]Electronic voting substituted roll-call voting as the only voting procedure in which the MEPs' individual ballots are recorded. Electronic voting is the default practice at the European Parliament, as it encompasses all final legislative votes since 2009, those in which a qualified majority is required, those in which there is no clear visual majority, and those for which any EPG or any group of at least 40 legislators previously requested it.

[10]The sample of non-alphabetically seated groups is composed by: EFD, EFDD, ENF, GUE/NGL, IND/DEM, ITS, UEN. The Greens (Verts/ALE) changed their seating organization to non-alphabetical in the beginning of Term 8.

all MEPs sat alphabetically during our studied period.[11] Throughout the studied period, the European Parliament had an average of 755 legislators, varying with the access of new member states to the Union. The compliance rate with the alphabetic seating rule might vary across groups and time.[12] The explanation for non-perfect adherence to the seating rule within the “alphabetical groups" is explained by the fact that the rule itself allows for members to occupy another seat for “technical or organizational proposes".

Similar to Harmon, Fisman and Kamenica (2019), we illustrate the predictive power of the alphabetical rank on the seating rank in Figure 1.2. It plots the within-EPG alphabetic rank and the within-EPG seating order for two different groups, one that adheres to the seating rule (Panel A) and one that does not (Panel B). In addition, individuals with prior working experience in interest groups are identified. The sample used in our analysis is determined by the change in the seating pattern depicted in Panel A. The dots on the left-hand side of Panel A depict those MEPs that sit in the front rows of their group, who clearly do not adhere to the alphabetic seating rule. We identify those as the EPG leaders. The dots on the right-hand side represent those MEPs that do sit alphabetically within the seats designated for their EPG. Those are the non-leader MEPs. Lastly, Panel B contains dots representing MEPs belonging to an EPG that does not adhere to the alphabetic seating rule. Our analysis is restricted to non-leader MEPs belonging to alphabetically sitting EPGs. Furthermore, we can visually observe how the seating distribution of legislators with prior experience in an interest group is not spatially nor alphabetically clustered.

1.3 Data

1.3.1 Plenary sessions

We collect the complete record of electronic votes at the European Parliament between June 2004 and May 2019 from each plenary session summary report. This dataset contains all electronically cast ballots for each MEP together with information on the motions' characteristics, such as the subjects covered and the committees involved. We combine this voting information with the MEP's corresponding plenary seating arrangement, published before each plenary session in the European Parliament's website.[13]

[11] ALDE places part of its leaders in an alphabetic manner. We consider these alphabetically seated leaders as part of our sample of interest, pooling them with the rest of alphabetically seated non-leader members. For simplicity, we refer to them also as non-leaders MEPs.

[12] The compliance rate is the correlation between the within-EPG alphabetical and seating rank. The average correlation across all voting dates is 0.92 in our sample of non-leaders from alphabetically organized EPGs.

[13] In the rare event that no seating plan was available for a particular plenary session, we take the preceding seating plan corresponding to the same venue as reference.

1.3.2 MEPs background

The legislators' biographical information comes from two different sources publicly provided by the European Parliament, namely the MEPs' personal profiles and their résumés. First, we collect the legislators' personal characteristics, such as age, sex, nationality and national party, and their roles in the internal organization of the Parliament (e.g., working committees, EPG positions and procedure rapporteurships) from the European Parliament Directory. Second, we put together the biographical records of all the MEPs who took office at any point in time during the 6th, 7th and 8th legislative terms, using their submitted résumés upon the start of their mandates.[14] The information contained in the résumés, initially collected by the European Parliament, was retrieved from the watchdog *Parltrack*. Using the information contained in these résumés, we identify the legislators' educational and professional background.

We identify those MEPs who studied at a "Top 500" university, measured using the 2003 Academic Ranking of World Universities, as a proxy of education excellence as in Fisman et al. (2015). We further characterize MEPs using their professional experience. We use three main measures to classify our legislators, namely their labor profile, skill level, and topics of expertise. Regarding the first measure, we start by classifying the legislators' working spells with the same categories used by the European Parliament: political, professional, or academic. We assign each parliamentarian to a category by selecting that of the most repeated type of work spell after weighing them linearly by the duration of each spell. We use a supervised Random Forest algorithm to fill working spells that were not classified by the European Parliament under any of these three categories.[15]

Regarding the legislator's skill level, we use a keyword matching algorithm to capture those spells that reflect high levels of responsibility.[16] We then define each parliamentarian as having or not having managerial skills, following the same methodology used to assign a labor profile. Lastly, we assign each legislator the topics in which they gained expertise prior to entering parliament, so as to be able to rule out any potential confounding effects coming through a better knowledge of the subjects voted upon. We do this in two stages. First, using the educational and professional background of all legislators, we classify each legislator using the 14 different categories proposed in Yordanova (2009) and Daniel and Thierse (2018).[17] Next, using all 48 different predefined subjects attached to each motion voted in parliament, we select those that best map into each of the 14 expertise categories.

[14]Despite being voluntary, a vast majority of the MEPs (81%) submitted their résumé. We hand-collect the biographical information of the remaining MEPs.

[15]We use as training dataset the curricula submitted during the terms 8th and 9th, as they were classified by the European Parliament under these three categories. The algorithm has a 5% error rate.

[16]Examples of the keywords used are CEO, board member, manager, founder, director, minister, secretary general, rector, dean, etc.

[17]We thank the authors of both studies for kindly providing their data, covering the 6th and 8th parliamentary terms. Following their directions, we hand-coded the same information for the 7th term.

Table 1.15 in the Appendix displays such mapping.

1.3.3 Interest Groups

The other fundamental source of information is provided by the EU Transparency Register. This voluntary register, created by the European Parliament and the European Commission in 2011, lists those organizations interested in influencing the EU decision-making process. Despite being voluntary, both the European Parliament and the European Commission require individuals to be listed in the register in order to access its facilities and to participate in a diverse range of activities that they promote, i.e. public consultations and expert groups, or to contact high-level decision-makers.[18]

For 2018, the register encompasses around 12.000 entities, with a total lobbying budget of €2.38 billion and almost 30.000 employees. From this source, we build a dataset with more than 17.000 entities registered at any point in time between 2016 and 2019,[19] including information on each organization's lobbying budget, policy interests, and sectors of activity. We use this dataset to extract the list of all organizations that have expressed interest in EU policy-making, and match them with the employers names found in the MEPs' résumés. We employ a keyword matching algorithm using a wide variety of patterns, such as stemmed words, the interest groups' websites, and different versions and translations of their registered names. The overall matching rate is 85%, computed using a hand-coded sample. A total of 28% of the MEPs in our sample were found to have worked for an interest group at some point before taking up office, ranging from short working spells on regional NGOs to high-level consulting jobs in lobbying firms.

Lastly, and crucial for our analysis, we are interested in identifying those motions that can be considered to be of importance for the economic activity of the interest groups identified in our sample. To do so, we rely on the 48-policy subject categories that the European Parliament assigns to each motion, linking them to each interest group.[20] The result of the hand-coded linkage between policy subjects and interest groups is the indicator variable *Relevant*, which allows us to distinguish which votes are of relevance to each interest group. To construct this variable, we use information scattered over different sources, such as the revealed issues of interest reported in the EU Transparency Register, the issues covered during the meetings with high-level officials from the European Commission, and their activity description from their website, among others.

Table 1.16 in the Appendix shows the share of interest groups that are assigned to

[18]For further information, please refer to the Annual Report on the operations of the Transparency Register (2019) and to Rule 11 in the Rules of Procedures of the European Parliament.

[19]We implicitly assume that those organizations registered at least once in the register were always interested in EU policy-making.

[20]The aforementioned level of disaggregation was selected to correctly match the MEPs' curricula information. For further details on the policy topics classification, see the EP Legislative Observatory.

each subject and their share over the total number of votes cast. While our main analysis is conducted using a single subject of interest per interest group, in Table 1.19 in the Appendix, we provide evidence that our main result holds when assigning each interest group with up to 3 relevant subjects.

1.4 Descriptive Statistics

Table 1.1 gives some descriptive evidence of how legislators in the sample used for our analysis, i.e., non-leaders affiliated to alphabetic seating groups, compare in a set of observable characteristics to their party leaders and to members of non-alphabetic groups. On our main sample, we identify 5 large groups, namely EPP, S&D, Greens, ECR, and ALDE, with 1,703 MEPs in their ranks. These MEPs cast 55.36% of all ballots at the European Parliament during the 6th, 7th, and 8th legislatures.

Panel A displays information on legislators' individual characteristics. Compared to their leaders, our sample of MEPs is characterized by a higher share of women (37% of the votes cast), younger cohorts, and with a lower proportion of members having studied in a top ranked education institution. Note that no large differences in these measures appear between MEPs in our sample and those affiliated to non-alphabetic seating groups.

Panel B presents the roles held in Parliament for each subsample. MEPS who seat alphabetically go marginally less often to vote compared to their party leaders, but do so more frequent than non-alphabetic members. They also hold less rapporteurships and positions in working committees than their leaders. This comes as a result of their novel status, with 57% of the votes cast by first-term members. Alternatively, we can observe how our sample of members are more actively involved in the parliament than those legislators from non-alphabetic groups.

Panel C reports information on the legislators' previous working experience. The predominant career profile among European Parliament legislators in our sample of interest is a political one rather than a professional or academic profile (69%, 27% and 3%, respectively), with similar shares in each of those categories in the other two samples. Legislators in our sample are further defined by having a median working profile, both in terms of experience and managerial status, when compared to their leaders and to members of non-alphabetic groups. Similarly, their average number of prior employment spells, 12.2, represents a mid-ground between their party leaders and those legislators in non-alphabetic groups. Key to our study is that MEPs' résumés are exhaustive, something that can be visually verified by comparing the legislators' mean age and years worked.

Panel D details the information about the legislators' prior interest group experience. We can notice how legislators with such experience are not equally distributed across the three samples. In our main sample, 28% of the legislators have working experience in

at least one interest group. Such MEPs are more prevalent among the party leaders of alphabetic seating groups, with 31%, and less among non-alphabetic EPGs, with 19% of their members. Nevertheless, the share of votes considered to be relevant to the economic activity of the interest groups that employed those legislators is similar across the three subsamples (5-6%).

Table 1.2 provides some descriptive evidence on the type of interest groups represented in our sample of non-leaders in alphabetical seating groups. The average interest group is a Belgium-based NGO, with on average 15 employees, 2 of which can access the European facilities and with an average lobbying budget of 500.000€. Furthermore, the sample used contains a wide variety of interest groups, ranging from small to very large interest groups, as highlighted by the large budget and employees' standard deviations.

1.5 Empirical Strategy

We are first interested in examining the extent to which MEPs' voting behavior is influenced by being placed adjacent to a colleague with working experience in an interest group using the following model:

$$Agree_{iv} = \alpha + \beta_1 Peers\ IG_{iv} + \eta_{iv} \tag{1.1}$$

where $Agree_{iv}$ is a variable capturing the fraction of legislators seating to the left and to the right of the focal legislator i during vote v casting the same vote as i. $Peers\ IG_{iv}$ is the fraction of adjacent legislators to the focal legislator i during vote v who used to work for an interest group before joining Parliament.[21]

To interpret β_1 as the causal effect of seating beside a colleague with previous interest group experience, we need legislators not to be able to choose where to sit; otherwise, some of their unobserved characteristics might correlate both with their voting behavior and their previous professional experience, biasing our estimation of β_1. We address this concern by restricting our attention to those members who sit in an alphabetical order. Despite the high compliance rate with the alphabetic seating rule, as shown in Section 1.2, we estimate both the intention-to-treat (ITT) and the average treatment effect of the compliers (LATE) instrumenting the group of individuals that sit adjacently to the focal MEP using the individuals whose surname is adjacent in the group's alphabetic rank. Hence, $Name\ Peers\ IG_{iv}$ is the fraction of legislators who previously worked at an interest group, and whose surnames are adjacent to that of the focal MEP i in her EPG's alphabetic list in a given vote v.

[21] MEPs seated at the beginning or at the end of their rows, as well as those seated by an aisle, are coded as only having one seat next to them instead of two.

A concern when using surname contiguity as an instrument for seat adjacency is that the former might be confounding other unobserved heterogeneous characteristics that cause legislators to vote in a similar way, such as having similar background. Using a dyadic approach, Harmon, Fisman and Kamenica (2019) assess such concern by showing that, after conditioning for party affiliation and surname similarity controls, surname adjacency between two MEPs does not predict their shared characteristics, such as shared nationality, similar education, freshman status, or gender. Using their results, in our preferred specification we control for surname similarity by using the fraction of adjacent legislators sharing the same surname as the focal MEP and the absolute alphabetic rank across EPGs and terms. These two controls help us mitigate unobservable characteristics shared by the focal and peer legislators.

In addition to the name similarity controls, we further include a comprehensive set of controls to capture any other type of characteristic of the focal legislator and her group of peers that might affect their voting agreement, together with fixed effects by EPG-Term, plenary sessions since the term started, procedure type and vote subject. Section 1.A in the Appendix includes the list with all the controls introduced in our specifications and their descriptive statistics are reported in Table 1.17 in the Appendix.

Next, we analyze whether the effect captured by β_1 depends on whether the subject of the motion being voted on is related to the adjacent legislators' former interest groups. To that end we introduce a new variable that identifies whether any of the subjects of the proposal being voted are related to the interest group in which the adjacent colleagues used to work, *Relevant*. Importantly, we code this variable only for the interest groups identified in our sample. Thus, this variable only takes a value of 1 if any adjacent MEP worked for an interest group before taking office; it takes a value of 0 when no adjacent legislator has experience in an interest group, or when the voting subject is not related to their interest group's sector of activity. Thus, we estimate the following fully saturated model:

$$Agree_{iv} = \alpha + \gamma_1 Peers\ IG_{iv} + \gamma_2 Peers\ IG_{iv} \times Relevant_{iv} + \epsilon_{iv} \tag{1.2}$$

as in Equation 1.1, we instrument Equation 2.1 using *Name Peers* IG_{iv} and *Name Peers* $IG_{iv} \times$ *Relevant*, in a twin first stage regression setting. We cluster all standard errors at the legislator level.

1.6 Results

We present our first set of results in Table 1.3. Columns 1 to 5 display the ITT estimates from equation 1.1, using $Name\ Peers\ IG$ instead of $Peers\ IG$ and progressively including

different fixed effects and individual and peer controls. Our first coefficient of interest, present in column 1, is estimated using a specification that does not include any fixed effect nor control variables. It indicates that there is a statistically significant increase of 3.5 percentage points in the probability of MEPs casting the same ballot as their alphabetic adjacent peers when all of them have professional experience in an interest group. By including EPG-by-Term and plenary session fixed effects and name similarity controls, we then account for the possibility that those effects might come from a specific EPG at a given legislative term, from some sort of temporal trend, or from name similarity conditions. The effect on the agreement probability is still statistically significant, while attenuated to an increase of 2.07 percentage points. In Column 3, we further control by some vote characteristics, namely by the procedure type and the vote subject, finding a similar effect of 2.06 percentage points.

In Column 4, we introduce focal legislators' characteristics, reducing the average probability of casting the same ballot as those surname adjacent MEPs with prior experience in an interest group to 1.27 percentage points. Introducing peer related controls in Column 5 produces a considerable drop in the probability of co-voting to 0.66 percentage points, and the coefficient becomes statistically insignificant.

Column 6 introduces our main regressor of interest, *Name Peers IG* $\times$ *Relevant*. It captures the additional effect of voting on a motion deemed relevant to the former employer of alphabetically adjacent MEPs on their probability of co-voting. It can be interpreted as the additional effect of being adjacent in the alphabetic list to a legislator who used to work for an interest group, when the subject of the motion is related to that group's economic activity. When the motion subject is not of interest to the peers' former employers, *Name Peers IG*, the agreement rate is smaller and not precisely estimated. This is not the case when the subject at stake is relevant to the peers' former interest group. In that case, *Name Peers IG* $\times$ *Relevant* significantly increases the probability of vote coincidence, by 0.74 percentage points.

Compared to those MEPs with no adjacent former interest group's legislators, surname adjacency to legislators with prior interest group exposure when the vote is deemed to be relevant to their interest groups increases the probability of casting the same ballot by 1.88 percent. The magnitude of this effect is 16% and 44% the size of the effects found for being name adjacent to the rapporteur and shadow rapporteur of the motion, respectively.[22] Given that the primary task of a rapporteur, and shadow rapporteurs, is to convince other legislators to vote like them on the motion they represent, we argue that former interest group members have a sizable influence on their adjacent colleagues.

Finally, Column 7 provides an estimate of the LATE using both regressors of interest.

[22]Table 1.20 displays Table 1.3 together with the coefficients for both focal and peer rapporteur and shadow rapporteurs, and for whether both focal and peer MEPs are from the same national party. Our main effect explains 43% of the variation in co-voting with a colleague from the same national party.

The high predictive power of the instrument is displayed in Table 1.18, which reports the results of the two first stages using the same controls and fixed effects as the specification in Column 7. Compared to Column 6, we can appreciate how both *Peers IG* and *Peers IG*Relevant* are similar in magnitude to their surname counterparts, as a result of the strong first stages. We find an increase in the average probability of casting the same ballot as the adjacent MEPs when voting on a subject deemed of relevance to their interest groups by 1.72 percentage points, or 2.40 percent when compared to those legislators with no adjacent former interest group member.[23] This effect corresponds to 21% or 57% of the influence exerted by an adjacent rapporteur or shadow rapporteurs, respectively.[24,25]

We are now interested in understanding the potential mechanisms that are at play when former interest group employees turned-politicians are able to persuade their colleagues to vote like them. To that end we shed light on which type of MEPs are more susceptible to following their colleagues with past experience in an interest group. We further explore the channels through which these legislators affect voting behavior, such as voting mobilization, the emphasis on high stake votes, the importance of the connection persistence and various interest group's characteristics.

1.6.1 MEPs' characteristics

We want to understand which personal characteristics define an MEP as more susceptible to be influenced by colleagues with interest group background. We first analyze whether the gender of the focal legislator plays a role. We reproduce Columns 5 to 7 from Table 1.3 on two different samples depending on the gender of the focal legislator. Results reported in Table 1.4 highlight that the effect on the agreement probability is driven entirely by women being affected by their seating colleagues with experience in an interest group, while no effect is found for male legislators.

Another group of legislators that may be prone to the influence of their colleagues' previous professional experience are first-term elected legislators. Several reasons might lie behind such behavior, ranging from not being familiar enough with most subjects that are voted upon in the Parliament to their higher willingness to please more tenured colleagues. This hypothesis is tested in Table 1.5, in which we follow the same approach as before, splitting the sample into those MEPs that have been present for more than one legislative

[23] We show in Table 1.21 that such influence is not present in cross party neighbors.

[24] Relevant for the consideration of the magnitude of our effects is the fact that seating adjacency, by itself, already increases the probability of *agreeing* by 0.6 percentage points (Harmon, Fisman and Kamenica, 2019).

[25] We show in Table 1.22 how legislators who previously worked in an interest group not only affect their closest peers, but also those at higher distances, with a decaying influence as distance increases. In the same line, Table 1.23 shows that using row-aggregated information produces consistent results with our main specification. In Table 1.24, we provide evidence that our benchmark results are not sensitive to different clustering choices.

term, and those who just got elected, whom we label as first-termer. While Columns 1 to 3 indicate that the agreement rate of more tenured MEPs with their sitting neighbors is not affected by the neighbors' background in an interest group, the agreement of first-term MEPs does show an effect. Focusing on the results in Column 6, the agreement rate of first-term MEPs with their seating colleagues when all of the neighbors have worked in interest groups increases by 2.17 percentage points. This estimate is statistically significant at 5% level and corresponds to a 3% increase over the average agreement rate.

While legislators with prior experience in interest groups affect their peers, such possibly partisan influence may be easily spotted, and avoided, by other legislators with similar professional backgrounds. Table 1.6 tests this hypothesis by subdividing the sample used into those legislators who previously worked for an interest group (Columns 1-3), and those who did not (Columns 4-6). It shows that those legislators who worked for an interest group before entering parliament are not influenced by their peers' who also worked for an interest group. Meanwhile, the agreement rate of MEPs with no ties to interest groups and their seating colleagues when all of the neighbors have worked in interest groups increases by 2.17 percentage points, which corresponds to a 3% increase over the average agreement rate.

Similarly, legislators with expertise in the motion voted on might be more likely to follow their own voting rationale, given their broader knowledge, and avoid their neighboring colleagues' influence. Table 1.7 tests this hypothesis by subdividing the sample used into those legislators with expertise, and those with no expertise on the subject of the motion being voted . It shows that legislators with prior interest group experience exert influence only on legislators lacking expertise on the subject of the motion voted on. No effect is found when the focal legislator has expertise on the motion voted upon. As an alternative measure of expertise, we use the appointment to the working committee responsible for drafting the motion voted on. Using that new measure of expertise, Table 1.25 shows qualitatively similar results.

These results indicate that not all MEPs are affected in the same way by their seating colleagues' previous professional experience in an interest group. Specifically, we find that female and first-term legislators are more susceptible to casting the same ballot as their seating neighbors when those neighbors have worked for an interest group in the past, but only during motions related to the group's economic activity. Moreover, our results show that those legislators who also have experience in an interest group and have expertise on the subject of the voted motion, do not coincide in their voting behaviour with their seating colleagues with interest group background.[26]

[26]We show in Table 1.26, using an ITT approach, that legislators significantly influence their peers when the topic is relevant for their former interest group, while not when they have academic knowledge on the topic.

1.6.2 Voting mobilization

We turn now to analyze how the legislators' ballots are actually influenced. Under the implicit assumption that legislators who previously worked for an interest group have a clear stance on those motions relevant to their previous employers,[27] their objective is to mobilize their network to vote in favor or against specific motions along their previous employer's economic activity. Using the specification in Equation (2.1), we start by estimating whether being in close proximity to a legislator with prior experience in an interest group affects the legislator's probability of abstaining on relevant votes.

We use an indicator variable taking a value of 1 if the focal legislator i casts an abstention ballot in vote v and of 0 otherwise. Columns 1-3 in Table 1.8 display the results from such estimation. We can see how seating adjacent to a legislator with interest group background does not have on average any effect on voting abstention, while it does have an effect when the motion is relevant for the interest group in which the neighboring legislator used to work. The effect, although small in absolute magnitude, predicts that legislators seating adjacent to a colleague with professional experience in an interest group related to the subject being voted on are on average 9% less likely to abstain on a given vote. However, the joint significance test of the linear combination of both point estimates shows that the overall effect is not statistically different from 0 at standard significance levels.

We have just shown how indeed those legislators who worked for an interest group before entering parliament affect their peers' voting behavior out of abstention only when the motion voted on is relevant for their former employer. This influence is possible because the limited party line enforcement at the European Parliament reduces the individual cost of casting a vote instead of actively abstaining. Our results seem to indicate that legislators with past professional experience in an interest group affect their peers when they are *de facto* in the chamber.

In the same direction, we could expect that they would also mobilize their network to participate in the voting process, as that would increase their support for a specific motion. Columns 4-6 in Table 1.8 display the analogous analysis for MEPs' absenteeism. We estimate Equation (2.1) using as the dependent variable an indicator variable taking a value of 1 when the focal legislator i was absent during vote v, and a 0 otherwise. Being designated to sit next to a legislator with prior interest group experience does indeed decrease the focal legislator's probability of being absent during the vote by 1.15 percentage points. Having in mind that MEPs in our sample are on average absent for 13 percent of the votes, the effect implies a decrease from the mean absenteeism rate by

[27] In our sample, we can observe how legislators have a clearer stance in those votes deemed to be relevant for their former employers (they vote yay or nay, in 86% of the votes when relevant and 85% when not relevant, as compared with the average baseline likelihood, 84%).

8.7 percent.[28]

1.6.3 High-stakes votes

We now want to understand whether the influence of those legislators with experience in interest groups is stronger in high-stakes situations. We rely on different vote characteristics to identify these type of situations.

First, to infer a motion's relative importance, we turn our attention to whether it concerns the budget of the Union or not. We consider this indicator to be a good proxy for high-stakes situation as such motions are part of the budgetary procedure, determining how the entire annual EU budget will be spent. Indeed, more than 16% of ballots in our sample refer to votes on the budget of the Union. Table 1.9 reproduces our preferred specification for proposals concerning the budget of the Union and for those unrelated to it. Both when voting on budget and non-budget related motions, legislators are influenced by being in close proximity to colleagues who worked for an interest group and the motion is relevant for their former employers. For instance, if we compare Columns 3 and 6, we can appreciate how the additional effect of having all seating neighbors with experience in an interest group when the topic is relevant for any prior employer, increases the probability of casting the same ballot by 1.6 percentage points in the case of non-budgetary votes and by 3.66 percentage points when deciding on budgetary matters. Both effects are statistically significant at the 5% level and, when compared to their corresponding average agreement rates, the probability of voting like the seating peers increases by 2.3% for non-budget votes and a 5% for budget-related motions.

A second type of vote feature we explore is whether the effect of these legislators depends on the motion passing margin. While using budget related motions to proxy high-stakes voting situations captures the relative importance of the motion with an intrinsic feature, the passing margin of a voted procedure attempts to measure high-stakes situations using an ex-post measure of the acceptance of the procedure by the chamber. Table 1.10 highlights that sitting next to legislators who previously worked for an interest group does not have any effect on the probability of co-voting along the three winning margins considered, namely winning by 1, 5 or 10%.

Overall, all these results suggest that legislators who previously worked for an interest group invest significant effort in persuading their colleagues in close proximity during budget related votes, but do not appear to do so during highly contested votes.

[28]Table 1.27 shows how the influence of these MEPs is similar during voting amendments and final votes. Similarly, Table 1.28 shows that former interest group members do not influence legislators' voting corrections or intentions.

1.6.4 Connection persistence

While the preceding section contained results providing evidence that MEPs' voting behavior is highly affected during high-stakes votes by their seating neighbors who worked in an interest group, we now explore whether these effects change as the group of legislators spend more time together. One could expect that the impact of legislators with prior interest group experience on their colleagues would evolve over time as the individuals in the group get to know each other. On the one hand, seating next to the same colleagues for long periods of time could facilitate the exchange of ideas, which in turn would make them more alike in their voting process. In our case, this would allow legislators with a prior experience in an interest group to draw adjacent legislators closer to their views, as they have shared many plenary sessions. On the other hand, the opposite effect could play a role too; legislators might learn about each other's point of views and hidden interests, and as a result avoid co-voting with them. In our case, this would imply that the ability of those legislators who worked in an interest group to affect their peers' ballots would decrease over time as their peers learned about their inclinations.

Table 1.11 shows the results of estimating Equation 2.1, adding as regressors the number of previous voting days in which each legislator has been assigned to sit adjacent to the same two other legislators, as well as the interactions with *Peers IG* and *Peers IG* $*$ *Relevant*.[29,30] Column 3 presents us with the fully saturated ITT model. As in the benchmark analysis, we can appreciate how MEPs who used to work in an interest group only influence their peers' voting behavior in those motions classified as relevant for their previous employer. Nevertheless, we can see how such effect decays as the group of MEPs get to know each other. It is important to note that all the regressions include time fixed effects, ruling out confounding effects with the parliamentarian learning process.

Column 4 introduces the fully saturated 2SLS model. Similar to the ITT case, we can appreciate how in the very first day together, these legislators influence their peers to vote like them by 2.76 percentage points, which represents a 3.9% increase over the average vote coincidence among seating neighbors. As time passes, and legislators continue being seated next to the same colleagues, their voting agreement drops, at a rate of 0.02 percentage points per voting day that they sit together. This effect implies that legislators would have to pass at least 276 voting days together for their agreement rate to be the same as that of a group of legislators without any of them having interest group background. If we consider that the average legislature in our sample has 182 voting days, and the average group of legislators sits together for 50 days, the results suggests

[29] We construct the corresponding instrument variable using the number of voting days that each legislator's surname was adjacent to the same two surnames in the party alphabetic list.

[30] Table 1.29 displays the results of using the number of plenary sessions that MEPs have been assigned together instead of voting dates, and similar results are found.

that the effect is considerably persistent over time, yet providing suggestive evidence that legislators learn from their peers' inclinations and eventually deviate from their voting behavior.

1.6.5 Interest groups' characteristics

We now shed light on whether the influence of those legislators with prior ties to interest groups varies depending on various interest groups' characteristics. We begin studying whether the effects we previously saw in Table 1.3 depend on the interest groups' business types. To that end, we define an interest group as private good if its legal status is business-related (e.g., companies and corporations which are not state owned) and public good, if its legal status is non-business-related, such as NGOs, trade unions and the like. Table 1.12 reports the results of our preferred specification. In Columns 1 to 3 (4 to 6), we use the baseline sample and drop those votes in which legislators sit adjacent to legislators with professional experience in a private good (public good) interest group. Results show that only legislators with experience in a public good interest group are able to influence their peers, achieving a 3.22 percentage increase in the agreement rate. No statistically significant results are found for private good interest groups. These results provide suggestive evidence on the influence that different interest groups have on their network, and highlight the relative importance public good interest groups have in the European lobbying sphere.

Second, we explore whether the location of the interest group's headquarters affects its relative influence. On the one hand, we might think that those interest groups located in Brussels, the city in which most EU bodies are based, would have a higher interest in EU policy and hence might mobilize their former employees-turned-politicians to exert a greater influence on their current colleagues. On the other hand, interest groups based in the European capital already have many other means to influence legislative voting and therefore might not utilize all their network. In contrast, interest groups located in their respective member states might not have such an extensive network, relying on placing their former employees in Parliament to influence EU policy making.

Results in Table 1.13 seem to provide evidence for the latter hypothesis. The results indicate that only legislators with prior experience in interest groups located somewhere other than in Brussels exert influence on their peers when the vote is deemed to be relevant for their former employers. Such effect amounts to 1.8 percentage points, or to a 2.5% increase in the agreement rate. No statistically significant effect is found for those legislators seated adjacent to colleagues who used to work in a Brussels-based interest group.

Third, we focus on whether the time that has passed since leaving an interest group

and the time spent in such an interest group affects the influence that legislators have on their peers. Figure 1.3 displays the average effect of all seating neighbors having worked in an interest group and voting on a motion related to the group's economic activity. More concretely, the left hand side panel shows how the influence of these reverse revolving doors' MEPs depends on how long ago they stopped working for their respective interest groups. There is generally a positive effect, with higher statistical significance for those legislators who finished such employment in the previous 4 years before entering parliament. Similarly, the right hand side panel shows that such influence is positive for any interest group tenure. Overall, both figures suggest that the influence legislators with prior interest group exposure have on their peers does not systematically depend on their interest group's tenure or the period that has passed since they stopped working for the interest group.

1.7 Conclusion

This paper estimates and provides evidence of the causal influence that members of the European Parliament who used to work for an interest group have on the voting behavior of legislators in their close network during specific motions. We do so by first identifying those members of the European Parliament with working experience in an interest group using detailed individual résumé information. We rely on the list of organizations registered as exhibiting interest in the European Union policy-making to classify legislators' former employers as interest groups. In order to avoid any of the classical obstacles to identifying causal effects stemming from social networks, we exploit the alphabetic seating rule imposed on most members of the European Parliament to construct an exogenous measure of network formation. Furthermore, we map each interest group's economic activity to one of the 48 subjects used to categorize each motion voted in the European Parliament. This allows us to identify motions of relevance to the interest groups which formerly employed legislators in our sample.

The results from our analysis show that when seated beside colleagues who worked for an interest group before entering Parliament and voting on a topic deemed to be important for such interest group, legislators do indeed increase the probability of co-voting with their peers. Such influence represents a 2.4% increase over the average agreement rate. These adjacent legislators do not exert any influence when the vote is not relevant for their previous employers. These effects are found to be driven by female MEPs, first-time elected members, and those that lack expertise on the subject being voted. Meanwhile, legislators who themselves worked for an interest group, or those with expertise on the motion, are not affected by such influence.

We shed light on how these legislators influence their peers' ballots by showing that

they reduce their seating neighbors' abstention ballots by 9% and their absenteeism by 6%. Additional insights are drawn in high-stakes votes, such as those referring to the Budget of the European Union, in which legislators with prior interest group ties are able to substantially increase the likelihood of their seating neighbors casting the same ballot, by 5%. Further results suggest, however, that legislators slowly learn from their seating neighbors' leanings and preferences, and accordingly start accounting for them by progressively reducing the number of ballots in which they agree.

To the best of our knowledge, this paper is the first one providing evidence of the distorting effects generated by reverse revolving doors on the legislative voting behavior of lawmakers.

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Figures and Tables

Figure 1.1: Strasbourg seating plan during the Plenary Session held on February 4th 2013

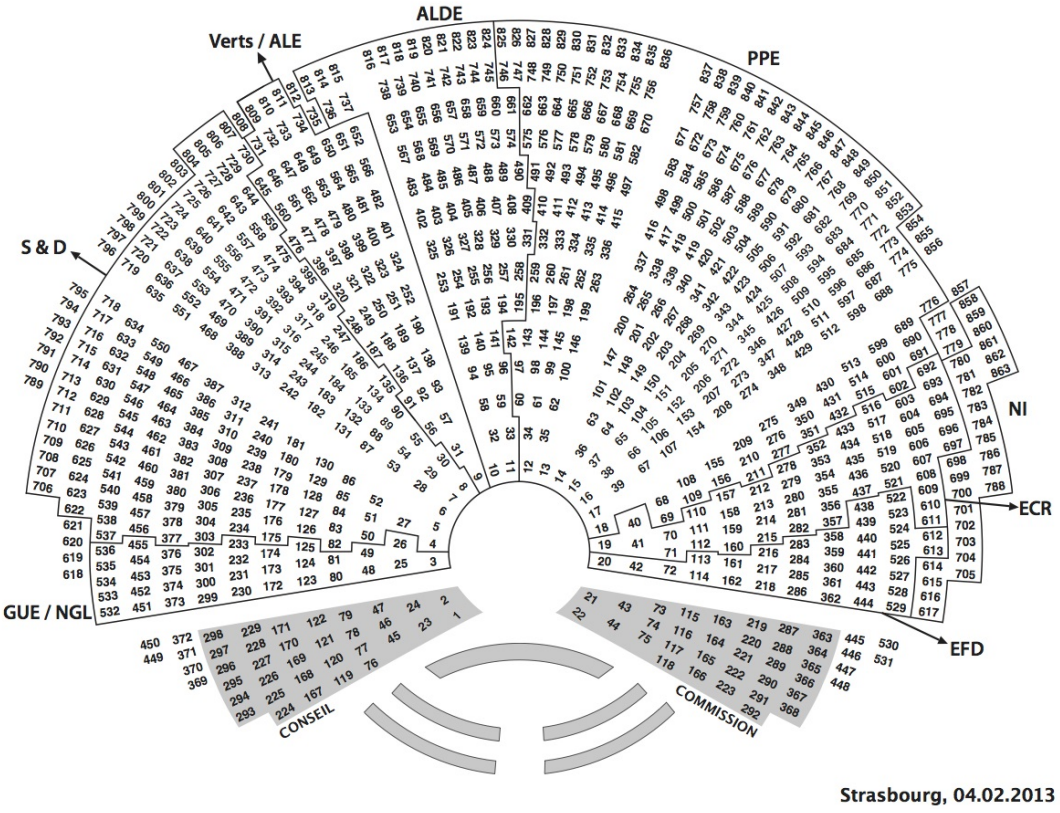
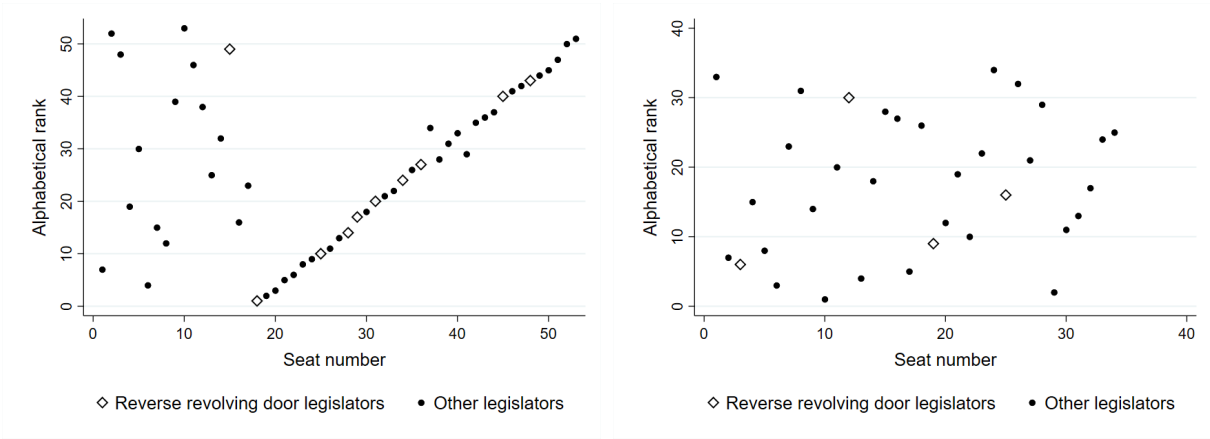


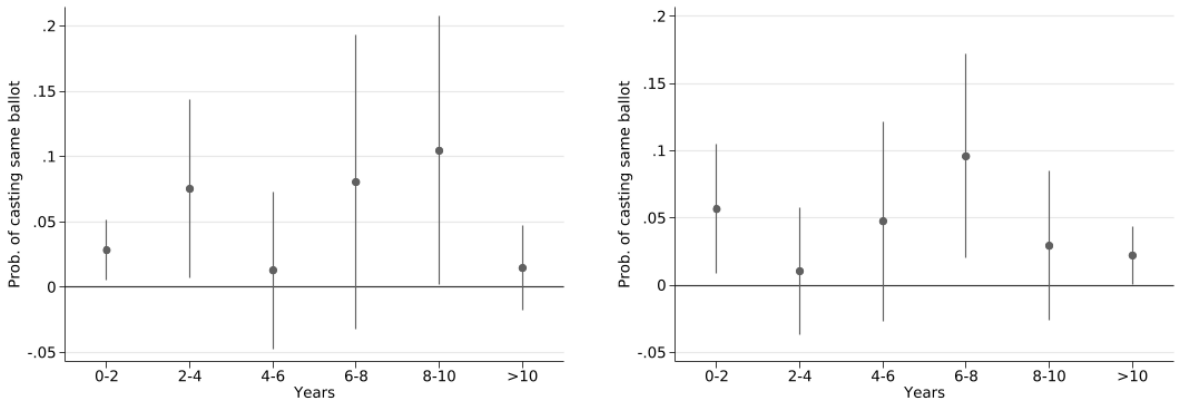
Figure 1.2: Seating and Alphabetical Rank



(a) ECR group (b) GUE/NGL group

Notes: This figure shows the correlation between within-EPG alphabetic rank and within-EPG seating rank. Subfigure 1.2a displays the correlation for the ECR group, which adheres to the alphabetic seating rule. Subfigure 1.2b looks at the GUE/NGL group, which does not adhere to the alphabetic seating rule. The data are plotted for a sitting held on February 5, 2013.

Figure 1.3: Temporal distribution of the effect of relevant reverse revolving doors on vote coincidence



(a) Last employed by an interest group (b) Experience in an interest group

Notes: This figure shows the results of estimating Equation (2.1) showing the results depending on the years since the employment of the legislators with interest group background ended and their years of experience. Subfigure 1.3a studies how this influence evolves vis-à-vis their adjacent peers' years since they last worked for an interest groups. Subfigure 1.3b focuses on how such effect depends on the years of experience adjacent legislators had in interest groups. The results shown in both subfigures correspond to the effect of seating adjacently to a legislator who previously worked for an interest group, when the topic is relevant for its former employer. A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. Confidence intervals represent the 95% confidence level.

Table 1.1: European Parliament sample comparison

	Non-leaders at alphabetic seating EPGs		Leaders at alphabetic seating EPGs		EPGs with no alphabetic seating	
	Votes cast	MEPs	Votes cast	MEPs	Votes cast	MEPs
Panel A: Legislators' characteristics						
Share women	0.37	0.36	0.33	0.33	0.31	0.28
Mean age	53.41	53.22	56.33	55.58	53.14	53.62
Share top ranked education	0.30	0.31	0.39	0.37	0.30	0.28
Panel B: Roles in Parliament						
Share first-term elected	0.57	0.58	0.26	0.34	0.66	0.67
Mean tenure at the EP	3.21	3.09	6.05	5.41	2.22	2.20
Share absence	0.13	–	0.12	–	0.15	–
Share rapporteur	0.001	–	0.002	–	0.000	–
Share shadow rapporteur	0.003	–	0.003	–	0.01	–
Mean number committee membership	4.96	–	5.37	–	4.65	–
Panel C: Legislators' prior experience						
Mean number of working spells	12.19	11.90	14.32	13.33	7.94	8.04
Mean years of working experience	24.68	24.39	26.69	26.29	22.68	22.86
Share managerial profile	0.27	0.26	0.30	0.28	0.23	0.23
Share political	0.69	0.70	0.78	0.78	0.56	0.57
Share professional	0.27	0.25	0.17	0.18	0.37	0.37
Share university	0.03	0.04	0.03	0.03	0.07	0.06
Panel D: Legislators' prior interest group experience						
Share worked for an interest group	0.28	0.28	0.31	0.31	0.21	0.19
Years experience in interest group	9.40	9.05	9.19	8.86	9.14	8.90
Interest group's share of relevant subject	0.05	–	0.06	–	0.05	–
Total	6,770,336	1,703	3,056,927	828	2,400,508	527

Notes: The table shows counts and shares in three different subsamples representing all the members of the European Parliament. Every member is coded as part of one of these samples or blocks. This is why, samples will overlap and will not add up to our full sample. Columns 1, 3 and 5 represent shares computed using all the votes cast, while Columns 2, 4, and 6, show those same shares computed using individual legislators. The sample selection criterion used to construct each of these three blocks is the same applied to obtain the sample used in the baseline analysis: we use only votes with an assigned rapporteur and containing at least one subject. We use legislators or their ballots who are non-leaders affiliated to alphabetic seating groups (columns 1 and 2), leaders affiliated to alphabetic seating groups (columns 3 and 4), and all members affiliated to non-alphabetic seating groups (columns 5 and 6). Moreover, for all three categories we use only members who sit besides at least one other legislator belonging to the same category.

Table 1.2: Interest Group's characteristics

	Mean	SD	Min	Max	N
Panel A: Business type					
NGOs	0.23	0.42	0	1	513
Academic institutions	0.19	0.39	0	1	513
Companies & Groups	0.18	0.39	0	1	513
Trade Unions	0.10	0.30	0	1	513
Other institutions	0.09	0.29	0	1	513
Trade and Business associations	0.06	0.24	0	1	513
Think Tanks	0.06	0.23	0	1	513
Transnational associations	0.04	0.19	0	1	513
Consultancies	0.03	0.17	0	1	513
Regional structures	0.03	0.17	0	1	513
Panel B: Headquarter's location					
Belgium	0.23	0.42	0	1	513
Germany	0.12	0.32	0	1	513
United Kingdom	0.11	0.32	0	1	513
Italy	0.07	0.26	0	1	513
France	0.07	0.25	0	1	513
Poland	0.04	0.21	0	1	513
Finland	0.04	0.20	0	1	513
Netherlands	0.04	0.20	0	1	513
Spain	0.04	0.20	0	1	513
Denmark	0.03	0.17	0	1	513
RoE	0.15	0.36	0	1	513
RoW	0.05	0.22	0	1	513
Panel C: Other characteristics					
Num. Employees	14.81	209.82	0	4750	513
Num. EP Accreditations	1.78	3.86	0	53	513
Lobbying Budget	512,445	1,131,297	0	10,000,000	513

Notes: The table displays the mean, standard deviation, minimum and maximum values for a set of interest group's characteristics. The interest groups used correspond to those identified in the résumés of non-leader MEPs affiliated with an alphabetic seating group.

Table 1.3: Average effect of reverse revolving doors connections on vote coincidence

	(1) OLS Agree	(2) OLS Agree	(3) OLS Agree	(4) OLS Agree	(5) OLS Agree	(6) OLS Agree	(7) 2SLS Agree
Name Peers IG	0.0350***	0.0207***	0.0206***	0.0126**	0.0066	0.0059	
	(0.0076)	(0.0067)	(0.0067)	(0.0053)	(0.0049)	(0.0050)	
Name Peers (IG * Relevant)						0.0074*	
						(0.0039)	
Peers IG							0.0080
							(0.0066)
Peers (IG * Relevant)							0.0092*
							(0.0049)
EPG x Term FEs	No	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	No	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	No	No	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	No	No	Yes	Yes	Yes	Yes	Yes
Name controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	No	No	No	Yes	Yes	Yes	Yes
Peers controls	No	No	No	No	Yes	Yes	Yes
Observations	6,770,336	6,770,336	6,770,336	6,770,336	6,770,336	6,770,336	6,770,336
Mean Agree	0.707	0.707	0.707	0.707	0.707	0.707	0.707
Joint p-value						0.0236	0.0254
F-stat 1							1056
F-stat 2							1308

Notes: This table shows the results of estimating Equation (2.1). We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.4: Average effect of reverse revolving doors connections on vote coincidence by legislator's gender

	Males			Females		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
	Agree	Agree	Agree	Agree	Agree	Agree
Name Peers IG	0.0041	0.0040		0.0074	0.0056	
	(0.0061)	(0.0062)		(0.0081)	(0.0082)	
Name Peers (IG * Relevant)		0.0016			0.0180***	
		(0.0051)			(0.0060)	
Peers IG			0.0053			0.0079
			(0.0081)			(0.0112)
Peers (IG * Relevant)			0.0020			0.0225***
			(0.0063)			(0.0076)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,248,656	4,248,656	4,248,656	2,521,680	2,521,680	2,521,680
Mean Agree	0.702	0.702	0.702	0.716	0.716	0.716
Joint p-value		0.440	0.437		0.0147	0.0185
F-stat 1			783.3			408.8
F-stat 2			820.9			587.5

Notes: This table shows the results of estimating Equation (2.1) using only male or female legislators. Columns 1-3 use those votes corresponding to male MEPs, while Columns 4-6 use only those corresponding to female legislators. We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.5: Average effect of reverse revolving doors connections on vote coincidence by legislator's first-term status

	Non first-termer			First-termer		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
	Agree	Agree	Agree	Agree	Agree	Agree
Name Peers IG	0.0064	0.0059		0.0072	0.0063	
	(0.0075)	(0.0075)		(0.0067)	(0.0067)	
Name Peers (IG * Relevant)		0.0052			0.0103**	
		(0.0063)			(0.0048)	
Peers IG			0.0077			0.0086
			(0.0098)			(0.0091)
Peers (IG * Relevant)			0.0063			0.0131**
			(0.0076)			(0.0062)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,871,766	2,871,766	2,871,766	3,898,570	3,898,570	3,898,570
Mean Agree	0.706	0.706	0.706	0.709	0.709	0.709
Joint p-value		0.223	0.224		0.0329	0.0367
F-stat 1			523.1			808.5
F-stat 2			711.8			919.9

Notes: This table shows the results of estimating Equation (2.1) using only non first-term and first-term elected legislators. Columns 1-3 use those votes corresponding to MEPs who are not in their first legislative term, while Columns 4-6 use only those corresponding to MEPs in their first legislative term. We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.6: Average effect of reverse revolving doors connections on vote coincidence by interest group background

	Interest group background			No interest group background		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
	Agree	Agree	Agree	Agree	Agree	Agree
Name Peers IG	0.0075	0.0078		0.0071	0.0060	
	(0.0091)	(0.0091)		(0.0060)	(0.0061)	
Name Peers (IG * Relevant)		-0.0024			0.0111**	
		(0.0067)			(0.0047)	
Peers IG			0.0105			0.0082
			(0.0123)			(0.0082)
Peers (IG * Relevant)			-0.0030			0.0135**
			(0.0087)			(0.0059)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,890,829	1,890,829	1,890,829	4,879,507	4,879,507	4,879,507
Mean Agree	0.718	0.718	0.718	0.703	0.703	0.703
Joint p-value		0.625	0.614		0.0148	0.0178
F-stat 1			296.3			928.3
F-stat 2			202.8			1534

Notes: This table shows the results of estimating Equation (2.1) using only legislators with and without interest group background. Columns 1, 2 and 3 uses the sample of votes in which the focal legislator worked for an interest group before entering parliament. Columns 4, 5 and 6 use the sample of votes in which the focal legislator did not worked in an interest group before entering parliament. We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.7: Average effect of reverse revolving doors connections on vote coincidence by motion expertise

	With expertise			Without expertise		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
	Agree	Agree	Agree	Agree	Agree	Agree
Name Peers IG	0.0100*	0.0095		0.0056	0.0049	
	(0.0060)	(0.0060)		(0.0052)	(0.0053)	
Name Peers (IG * Relevant)		0.0037			0.0091**	
		(0.0063)			(0.0046)	
Peers IG			0.0128			0.0066
			(0.0080)			(0.0070)
Peers (IG * Relevant)			0.0043			0.0116**
			(0.0077)			(0.0058)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,865,087	1,865,087	1,865,087	4,905,249	4,905,249	4,905,249
Mean Agree	0.709	0.709	0.709	0.707	0.707	0.707
Joint p-value		0.115	0.109		0.0238	0.0252
F-stat 1			783.9			1129
F-stat 2			1459			779.6

Notes: This table shows the results of estimating Equation (2.1) using only legislators with and without expertise in the subject of the motion voted on. Columns 1, 2 and 3 uses the sample of votes in which the focal legislator has clear expertise on the motion voted on. Columns 4, 5 and 6 use the sample of votes in which the focal legislator do not have such expertise. We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.8: Average effect of reverse revolving doors connections on voting abstention and absenteeism

	(1) OLS Abstain	(2) OLS Abstain	(3) 2SLS Abstain	(4) OLS Absent	(5) OLS Absent	(6) 2SLS Absent
Name Peers IG	-0.0010	-0.0009		-0.0086*	-0.0086*	
	(0.0016)	(0.0016)		(0.0047)	(0.0047)	
Name Peers (IG * Relevant)		-0.0017**			-0.0000	
		(0.0008)			(0.0038)	
Peers IG			-0.0012			-0.0115*
			(0.0021)			(0.0062)
Peers (IG * Relevant)			-0.0020**			-0.0000
			(0.0010)			(0.0047)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,881,658	5,881,658	5,881,658	6,770,336	6,770,336	6,770,336
Mean dep. variable	0.0229	0.0229	0.0229	0.131	0.131	0.131
Joint p-value		0.131	0.139		0.141	0.134
F-stat 1			1020			1056
F-stat 2			1236			1308

Notes: This table shows the results of estimating Equation (2.1) using as the dependent variable whether the legislator cast an abstention ballot or was absent during the vote. Columns 1-3 analyze the intensive margin of voting, using only those days in which the focal legislator attended the voting plenary. Columns 4-6 study the extensive margin of voting, i.e., whether the focal legislator attended the voting plenary. We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.9: Average effect of reverse revolving doors connections on vote coincidence by vote type

	Non-budget vote			Budget vote		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
	Agree	Agree	Agree	Agree	Agree	Agree
Name Peers IG	0.0062	0.0054		0.0073	0.0069	
	(0.0049)	(0.0049)		(0.0076)	(0.0076)	
Name Peers (IG * Relevant)		0.0070*			0.0222**	
		(0.0040)			(0.0102)	
Peers IG			0.0073			0.0092
			(0.0065)			(0.0101)
Peers (IG * Relevant)			0.0087*			0.0274**
			(0.0050)			(0.0124)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,651,802	5,651,802	5,651,802	1,118,534	1,118,534	1,118,534
Mean Agree	0.703	0.703	0.703	0.732	0.732	0.732
Joint p-value		0.0354	0.0376		0.0119	0.0119
F-stat 1			1055			977.1
F-stat 2			1290			598.1

Notes: This table shows the results of estimating Equation (2.1) using only votes that are not related to the budget of the Union and those which are. We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.10: Average effect of reverse revolving doors connections on vote coincidence by margin of victory

	(1) OLS Agree	(2) OLS Agree	(3) 2SLS Agree	(4) OLS Agree	(5) OLS Agree	(6) 2SLS Agree	(7) OLS Agree	(8) OLS Agree	(9) 2SLS Agree
Name Peers IG	-0.0013	-0.0008		0.0029	0.0031		0.0042	0.0041	
	(0.0082)	(0.0082)		(0.0073)	(0.0072)		(0.0067)	(0.0067)	
Name Peers (IG * Relevant)		-0.0042			-0.0015			0.0009	
		(0.0090)			(0.0071)			(0.0065)	
Peers IG			-0.0012			0.0040			0.0054
			(0.0109)			(0.0096)			(0.0088)
Peers (IG * Relevant)			-0.0053			-0.0018			0.0011
			(0.0112)			(0.0089)			(0.0081)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135,195	135,195	135,195	643,715	643,715	643,715	1,226,807	1,226,807	1,226,807
Mean Agree	0.693	0.693	0.693	0.686	0.686	0.686	0.683	0.683	0.683
Joint p-value		0.675	0.679		0.877	0.869		0.586	0.582
F-stat 1			963.6			980.7			1075
F-stat 2			787.3			904.2			1045

Notes: This table shows the results of estimating Equation (2.1) with different sample of votes depending on the margin of victory. The sample is divided into votes that were passed by a margin of 1% (Columns 1, 2, 3), 5% (Columns 4, 5, 6) and 10% (Columns 7, 8, 9). We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.11: Average effect of reverse revolving doors connections on vote coincidence persistence by voting days

	(1) OLS Agree	(2) OLS Agree	(3) OLS Agree	(4) 2SLS Agree
Name Peers IG	0.0060	0.0046	0.0037	
	(0.0050)	(0.0068)	(0.0068)	
Name Peers (IG * Relevant)	0.0073*	0.0073*	0.0164**	
	(0.0039)	(0.0039)	(0.0065)	
Vote days name adjacent	-0.0000	-0.0000	-0.0000	
	(0.0000)	(0.0000)	(0.0000)	
Name Peers IG * Vote days name adjacent		0.0000	0.0000	
		(0.0001)	(0.0001)	
Name Peers (IG * Relevant) * Vote days name adjacent			-0.0001	
			(0.0001)	
Peers IG				0.0052
				(0.0093)
Peers (IG * Relevant)				0.0225**
				(0.0089)
Vote days seat adjacent				-0.0000
				(0.0001)
Peers IG * Vote days seat adjacent				0.0001
				(0.0001)
Peers (IG * Relevant) * Vote days seat adjacent				-0.0002*
				(0.0001)
EPG x Term FEs	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes
Observations	6,770,336	6,770,336	6,770,336	6,770,336
Mean Agree	0.707	0.707	0.707	0.707
Joint p-value		0.125	0.0308	0.0306
F-stat (KP)				172

Notes: This table shows the results of estimating Equation (2.1) adding as regressors the number of previous voting days in which each legislator has been assigned to sit adjacent to the same two other legislators, as well as the interactions with *Peers IG* and *Peers IG* $*$ *Relevant*, and their correspondent instruments. We denote as joint p-value the test on the joint significance of all the variables displayed in the table (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. The reported F Statistics has been calculated following Kleibergen and Paap (2006). Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.12: Average effect of reverse revolving doors connections on vote coincidence by type of interest groups

	Public good interest group			Private good interest group		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
	Agree	Agree	Agree	Agree	Agree	Agree
Name Peers IG	0.0091*	0.0083		0.0029	0.0021	
	(0.0053)	(0.0054)		(0.0064)	(0.0064)	
Name Peers (IG * Relevant)		0.0092*			0.0084	
		(0.0048)			(0.0052)	
Peers IG			0.0110			0.0031
			(0.0072)			(0.0094)
Peers (IG * Relevant)			0.0118*			0.0121
			(0.0063)			(0.0076)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,835,465	5,835,465	5,835,465	4,831,995	4,831,995	4,831,995
Mean Agree	0.708	0.708	0.708	0.702	0.702	0.702
Joint p-value		0.00788	0.00841		0.187	0.191
F-stat 1			880.9			320.6
F-stat 2			894.3			396.9

Notes: This table shows the results of estimating Equation (2.1) dividing the sample used by the type of organization which employed legislators with interest group experience. Estimates in presented in Columns 1, 2 and 3 were produced using the baseline sample and dropping all votes of legislators who sit adjacently legislators with prior private good interest group experience. Analogously, Columns 4, 5 and 6 use the baseline sample after having dropped all votes of legislators who sit adjacently to legislators with prior public good interest group experience. We define private good interest groups as those whose legal status is business-related (e.g. companies and corporations which are not state owned) and public good interest groups as those with a non-business-related legal status, such as NGOs, trade unions and so on. A comprehensive set of controls at the focal and peer legislators is used in the analysis. We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.13: Average effect of reverse revolving doors connections on vote coincidence by the interest group location

	Brussels interest group			No Brussels interest group		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
	Agree	Agree	Agree	Agree	Agree	Agree
Name Peers IG	0.0131	0.0128		0.0052	0.0042	
	(0.0080)	(0.0081)		(0.0051)	(0.0052)	
Name Peers (IG * Relevant)		0.0023			0.0097**	
		(0.0084)			(0.0042)	
Peers IG			0.0259			0.0057
			(0.0166)			(0.0069)
Peers (IG * Relevant)			0.0039			0.0123**
			(0.0162)			(0.0053)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,140,485	4,140,485	4,140,485	6,305,187	6,305,187	6,305,187
Mean Agree	0.702	0.702	0.702	0.706	0.706	0.706
Joint p-value		0.164	0.164		0.0233	0.0252
F-stat 1			81.87			948.9
F-stat 2			91.74			1051

Notes: This table shows the results of estimating Equation (2.1) dividing the sample used by the location of the organization which employed legislators with interest group experience. Columns 1, 2 and 3 uses the sample of votes in which peer legislators did not worked at an interest group not based in Brussels. Columns 4, 5 and 6 use the sample of votes in which peer legislators did not work in a Brussels based interest group. We denote as joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 1.A Description of controls used for focal and peer legislators

This section presents the variables used as control in our main analysis, both for focal and peer legislators. We classify them into *Name controls*, *Focal MEP controls* and *Peers controls*.

i) *Name controls*: Owing to the possibility that surnames may represent the individuals, observable and unobservable, characteristics, such as socioeconomic background or family ties, in the spirit of Harmon, Fisman and Kamenica (2019), we control by the fraction of focal and individuals in the same group of peers sharing the same surname, and by the absolute alphabetic rank across EPGs and terms.

ii) *Focal MEP controls*: We characterize legislators using a wide set of controls. As for the legislators' personal characteristics, we control for their age, gender, national party, country of origin and whether they attended a top 500 university. As for the legislators' professional characteristics, we control for their years of professional experience before entering parliament, the total number of working positions, whether they have a managerial profile, whether their professional experience was conducted in the public, private, or academic sector, and their number of professional spells. We also control their topics of expertise, measured using Yordanova (2009)'s classification, and the number of such topics, as well as whether previously worked for an interest group and if the topic is relevant for such previous employers. Regarding their previous interest groups' characteristics, we control by whether they have their headquarters in Brussels, and by their average reported EU lobbying budget. As for the legislator's in parliament characteristics, we control for their freshman status, their share of previous dates absent, their role at their EPG, whether they are part of the alphabetically seated leader sector in ALDE, whether they are the rapporteur or shadow rapporteur in the specific procedure voted, whether their EPG had one of these figures, whether such procedure refers to their own country, and whether they were at the responsible and opinion committees of the procedure voted on. We further control by whether the motion voted upon was a final vote or an amendment.

iii) *Peers controls*: We characterize connections, i.e. adjacent (left and right) siting peers, by expanding the above mentioned variables. We include as controls the fraction of the adjacent peers in the same EPG as the focal, the fraction in the same national party as the focal, the fraction from the same country as the focal, the fraction with the same EPG role as the focal, the fraction with the same profession profile as the focal, the fraction with the same managerial profile as the focal, the

fraction with the same freshman status as the focal, the fraction with the same gender as the focal, the fraction having the same “Top 500" education as the focal, and the fraction of the peers in the same committee as the focal. We also use peer controls that are irrespective of the focal characteristics such as the fraction of peers with freshman status, the fraction of female peers, the fraction of peers with a Top 500 education, the fraction of peers with a managerial profile, the fraction of rapporteur and shadow rapporteur peers, the fraction of peers in the committee responsible or committee of opinion for the procedure voted on, the fraction of peers with expertise in the topics voted on, the fraction of the peers for which the procedure voted on is of national relevance, the number of peers (from 1 to 2), the average absenteeism rate of the peers, the average number of topics of expertise of the peers, as well as, the fraction of peers with an interest group based in Brussels, and the average EU lobbying budget of these interest groups. Additionally, using information from peers and focal legislators, we control for the standard deviation in their age, professional experience, number of positions at the European Parliament, number of working positions, number of topics of expertise, and absenteeism rate.

Appendix 1.B Additional tables

Table 1.14: Summary of samples by rapporteur presence

	Votes cast with rapporteur	Votes cast without rapporteur
Panel A: Voting distribution		
Electronically cast ballots	13,365,545	4,067,500
In favour	51.78	42.52
Abstained	3.49	3.84
Against	31.37	34.62
Absence	13.36	19.03
Panel B: Vote characteristics		
Average position on day voting order	40.10	35.52
Budget of the Union procedure	13.12	0.09
Legislative and Non-legislative procedure	38.32	2.13
Parliament resolutions and initiatives	48.56	97.78

Notes: The table shows counts and shares by whether a vote had a rapporteur assigned or not. It displays the absolute frequency of electronic ballots cast with and without rapporteur during the terms 6, 7 and 8. The distributions by vote outcome and by vote characteristics are expressed in percentages. The three type of procedure categories shown in Panel B are based on the procedure description present at the European Parliament website.

Table 1.15: Mapping of expertise and vote subjects

Variable as in Yordanova (2009)	Vote subjects
Business/Industry	Common commercial policy in general; Competition; Enterprise policy, inter-company cooperation; Free movement of goods; Free movement of services, freedom to provide; Industrial policy; Taxation
Economics/Finance	Common commercial policy in general; Competition; Economic union; Enterprise policy, inter-company cooperation; European statistical legislation; Free movement of capital; Monetary union; Taxation
Education	Common cultural area, cultural diversity; Education, vocational training and youth; Research and technological development and space
Farming	Agricultural policy and economies; Fisheries policy
Green ties	Agricultural policy and economies; Environmental policy; Fisheries policy
International relations	Common foreign and security policy; Development cooperation; Emergency, food, humanitarian aid, aid to refugees, Emergency Aid Reserve; Enlargement of the Union; Relations with third countries
Legal	Citizen's rights; Consumers' protection in general; EU law; Free movement and integration of third-country nationals; Fundamental rights in the EU, Charter; Institutions of the Union; Judicial cooperation; Justice and home affairs; Police, judicial and customs cooperation in general; Revision of the Treaties, intergovernmental conferences; Treaties in general
Local government	Common cultural area, cultural diversity; Regional policy; Tourism
Media	Information and communications in general
Medicine	Public health
Science/Engineering	Energy policy; Environmental policy; Information and communications in general; Research and technological development and space
Social group	Citizen's rights; Free movement and integration of third-country nationals; Fundamental rights in the EU, Charter; Social policy, social charter and protocol
Trade Union	Employment policy, action to combat unemployment; Free movement of workers; Social policy, social charter and protocol
Transport/Telecommunications	Transport policy in general

Notes: The table displays how the expertise topics, as in Yordanova (2009), map into the vote subjects at the European Parliament.

Table 1.16: Vote and interest groups share by procedure subject

Vote Subjects	Share votes	Share IGs	Num. MEPs	Extra subjects
Budget of the Union	16.52	0	0	2.068
Environmental policy	12.08	3.824	15	2.558
Social policy, social charter and protocol	10.24	4.706	17	2.032
Employment policy, action to combat unemployment	8.815	10.29	35	2.366
Agricultural policy and economies	8.577	3.529	12	2.361
Industrial policy	7.753	3.235	11	2.767
Institutions of the Union	6.804	0.588	3	2
Consumers' protection in general	6.757	1.765	7	2.673
Common commercial policy in general	6.728	0.882	4	2.433
Transport policy in general	6.221	3.824	14	2.359
Common foreign and security policy	5.296	3.824	16	1.886
Energy policy	5.218	3.235	11	2.638
Police, judicial and customs cooperation in general	4.871	0.294	1	2.253
Relations with third countries	4.812	0	0	2.123
Research and technological development and space	4.120	5.588	20	2.394
Enterprise policy, inter-company cooperation	3.697	3.529	14	2.468
Fisheries policy	3.672	0.588	2	2.195
Public health	3.596	4.706	19	2.426
Free movement and integration of third-country nationals	3.498	1.471	5	1.821
Regional policy	3.346	8.529	30	2.311
Economic union	3.187	0	0	2.125
Free movement of capital	3.080	8.529	31	2.133
Free movement of services, freedom to provide	3.050	0.294	1	2.561
Information and communications in general	2.993	16.18	55	2.292
Free movement of goods	2.836	0	0	2.781
Development cooperation	2.719	1.176	5	2
Economic growth	2.660	0	0	2.417
Citizen's rights	2.657	0.588	3	2.441
Monetary union	2.300	0.294	1	1.833
Taxation	2.203	0.588	2	2.122
Judicial cooperation	1.917	0	0	2
Fundamental rights in the EU, Charter	1.867	1.471	6	2.148
Competition	1.661	0	0	2.308
Cooperation between administrations	1.489	0.294	1	2.532
Enlargement of the Union	1.409	0.294	2	1.375
Education, vocational training and youth	1.406	27.35	95	1.933
Revision of the Treaties, intergovernmental conferences	1.249	0	0	1.400
EU law	1.130	0	0	2.163
Common cultural area, cultural diversity	0.814	1.176	4	2.222
Global economy and globalisation	0.766	0.294	2	1.789
Treaties in general	0.672	0.294	2	1.222
Free movement of persons	0.338	0	0	2
Emergency, food, humanitarian aid, aid to refugees, Emergency Aid Reserve	0.281	1.471	5	1.786
Tourism	0.231	0.294	1	1.143
European statistical legislation	0.223	0	0	1.429
Free movement of workers	0.126	0	0	2.857
Justice and home affairs	0.0851	0	0	2
Civil protection	0.0774	0.294	1	1.250

Notes: The table displays the share of votes by procedure subject in Column 1. Column 2 shows the share of legislators who previously worked for an interest group, and for which the subject is considered to be relevant, and Column 3 shows the total number of them. Column 4 displays the average number of subjects each procedure classified with a particular subject is accompanied by. The sample used is the same as in the main analysis, namely only votes with a rapporteur and cast by legislators identified as non leader in alphabetically organized groups with peers satisfying the same requirements.

Table 1.17: Summary statistics

	Mean	SD	Min	Max	N
Agree	0.71	0.38	0	1	6770336
Absention	0.02	0.14	0	1	6770336
Lobbyist Legislator	0.28	0.45	0	1	6770336
Ratio Relevant Topic (not political) (main)	0.01	0.07	0	1	6770336
Peers IG	0.28	0.33	0	1	6770336
Peers (IG * Relevant)	0.03	0.16	0	1	6770336
Name Peers IG	0.28	0.33	0	1	6770336
Name Peers (IG * Relevant)	0.03	0.17	0	1	6770336
Final vote	0.23	0.42	0	1	6770336
Expertise	0.28	0.45	0	1	6770336
Age	53.42	10.68	26	86	6770336
Rapporteur	0.00	0.04	0	1	6770336
Shadow Rapporteur	0.00	0.06	0	1	6770336
Part of the responsible committee	0.01	0.08	0	1	6770336
Part of the opinion committee	0.00	0.07	0	1	6770336
National law	0.00	0.01	0	1	6770336
National party	241.45	129.08	2	453	6770336
Country	16.07	7.85	1	28	6770336
EPG Role	4.87	0.50	2	5	6770336
Female	0.37	0.48	0	1	6770336
Part of the ALDE leader section	0.05	0.22	0	1	6770336
Freshman status	0.58	0.49	0	1	6770336
Number of professional positions	4.95	1.24	0	12	6770336
Rapporteur in the EPG	0.70	0.46	0	1	6770336
Top 500 education	0.31	0.46	0	1	6770336
Previous sector of activity	1.34	0.54	1	3	6770336
Professional experience	24.68	10.97	1	56	6770336
Managerial profile	0.27	0.45	0	1	6770336
Number of working spells	12.19	9.84	1	87	6770336
Share previous days absent	0.13	0.11	0	1	6770336
IG - Brussels HQ	0.05	0.20	0	1	6770336
IG - EU Lobbying budget	127203.57	447452.89	0	5002500	6770336
Number of expertise topics	11.01	5.95	0	31	6770336
National law (peers)	0.00	0.01	0	1	6770336
Freshman (peers)	0.58	0.37	0	1	6770336
Female (peers)	0.37	0.36	0	1	6770336
Managerial profile (peers)	0.27	0.33	0	1	6770336
Top 500 education (peers)	0.31	0.34	0	1	6770336
Rapporteur (peers)	0.00	0.03	0	1	6770336
Shadow Rapporteur (peers)	0.00	0.04	0	1	6770336
Part of the responsible committee (peers)	0.01	0.06	0	1	6770336
Part of the opinion committee (peers)	0.00	0.05	0	1	6770336
Number of peers	1.91	0.29	1	2	6770336
Expertise (peers)	0.28	0.36	0	1	6770336
Share previous days absent (peers)	0.13	0.08	0	1	6770336
IG - Brussels HQ (peers)	0.04	0.14	0	1	6770336
IG - EU Lobbying budget (peers)	129014.55	335746.82	0	5002500	6770336
Number of expertise topics (peers)	11.03	4.42	0	31	6770336
Same gender (peers)	0.53	0.38	0	1	6770336
Same EPG (peers)	0.96	0.14	0	1	6770336
Same national party (peers)	0.08	0.21	0	1	6770336
Same country (peers)	0.10	0.23	0	1	6770336
Same EPG role (peers)	0.93	0.21	0	1	6770336
Same freshman status (peers)	0.51	0.38	0	1	6770336
Same previous sector of activity (peers)	0.57	0.40	0	1	6770336
Same managerial profile (peers)	0.61	0.38	0	1	6770336
Same Top 500 education (peers)	0.57	0.39	0	1	6770336
Same position at the same committee (peers)	0.20	0.30	0	1	6770336
Age SD (peers)	9.43	4.98	0	34	6770336
Professional experience SD (peers)	9.73	5.14	0	33	6770336
Number of professional positions SD (peers)	1.03	0.65	0	6	6770336
Share previous days absent SD (peers)	0.08	0.06	0	1	6770336
Number of working spells SD (peers)	7.39	6.42	0	60	6770336
Number of Expertise Topics SD (peers)	5.29	2.81	0	20	6770336

Notes: The table displays the mean, standard deviation, minimum and maximum value for every variable used in the baseline regression. For further information, see Appendix 1.A.

Table 1.18: First stage estimates of name adjacency on seating adjacency

	(1) OLS Peers IG	(2) OLS Peers (IG * Relevant)
Name Peers IG	0.7507***	-0.0083***
	(0.0164)	(0.0020)
Name Peers (IG * Relevant)	0.0020	0.8007***
	(0.0051)	(0.0157)
EPG x Term FEs	Yes	Yes
Sessions since term started FEs	Yes	Yes
Procedure type FEs	Yes	Yes
Vote subject FEs	Yes	Yes
Name controls	Yes	Yes
Focal MEP controls	Yes	Yes
Peers controls	Yes	Yes
Observations	6,770,336	6,770,336

Notes: The table presents the estimates for the baseline first stage regressions. A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.19: Average effect of reverse revolving doors connections on vote coincidence using multiple topics of interest

	(1) OLS Agree	(2) OLS Agree	(3) OLS Agree	(4) OLS Agree	(5) OLS Agree	(6) OLS Agree	(7) 2SLS Agree
Name Peers IG	0.0350***	0.0207***	0.0206***	0.0126**	0.0066	0.0056	
	(0.0076)	(0.0067)	(0.0067)	(0.0053)	(0.0049)	(0.0050)	
Name Peers (IG * Relevant)						0.0049*	
						(0.0029)	
Peers IG							0.0076
							(0.0066)
Peers (IG * Relevant)							0.0061*
							(0.0036)
EPG x Term FEs	No	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	No	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	No	No	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	No	No	Yes	Yes	Yes	Yes	Yes
Name controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	No	No	No	Yes	Yes	Yes	Yes
Peers controls	No	No	No	No	Yes	Yes	Yes
Observations	6,770,336	6,770,336	6,770,336	6,770,336	6,770,336	6,770,336	6,770,336
Mean Agree	0.707	0.707	0.707	0.707	0.707	0.707	0.707
Joint p-value						0.0504	0.0540
F-stat 1							1052
F-stat 2							2023

Notes: This table shows the results of estimating Equation (2.1). We define interest groups to have up to three topics of interest. We denote as Joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.20: Average effect of reverse revolving doors connections on vote coincidence - Displaying rapporteur and national party's influence

	(1) OLS Agree	(2) OLS Agree	(3) 2SLS Agree
Name Peers IG	0.0066	0.0059	
	(0.0049)	(0.0050)	
Name Peers (IG * Relevant)		0.0074*	
		(0.0039)	
Peers IG			0.0080
			(0.0066)
Peers (IG * Relevant)			0.0092*
			(0.0049)
Rapporteur	0.0767***	0.0767***	0.0767***
	(0.0132)	(0.0132)	(0.0132)
Shadow Rapporteur	0.0306***	0.0306***	0.0308***
	(0.0085)	(0.0085)	(0.0085)
Peer Rapporteur	0.0834***	0.0832***	0.0832***
	(0.0184)	(0.0184)	(0.0184)
Peer Shadow Rapporteur	0.0305**	0.0302**	0.0302**
	(0.0123)	(0.0123)	(0.0123)
Same National party	0.0393**	0.0393**	0.0396**
	(0.0200)	(0.0200)	(0.0200)
EPG x Term FEs	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes
Name controls	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes
Observations	6,770,336	6,770,336	6,770,336
Mean Agree	0.707	0.707	0.707
Joint p-value		0.0236	0.0254
F-stat 1			1056
F-stat 2			1308

Notes: This table shows the results of estimating Equation (2.1). It is analogous to the Columns 5, 6, and 7, in Table 1.3, respectively. We denote as Joint p-value the test on the joint significance of the adjacency to a legislator with previous interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.21: Average effect of reverse revolving doors connections on vote coincidence using a cross-EPG sample

	(1) OLS Agree	(2) OLS Agree	(3) OLS Agree	(4) OLS Agree	(5) OLS Agree	(6) OLS Agree
Peer IG	-0.0005	-0.0021	-0.0013	0.0022	0.0006	0.0005
	(0.0118)	(0.0088)	(0.0088)	(0.0075)	(0.0077)	(0.0077)
Peer (IG × Relevant)						0.0010
						(0.0130)
EPG x Term FEs	No	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	No	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	No	No	Yes	Yes	Yes	Yes
Vote subject FEs	No	No	Yes	Yes	Yes	Yes
Name controls	No	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	No	No	No	Yes	Yes	Yes
Peers controls	No	No	No	No	Yes	Yes
Observations	582,833	582,833	582,833	582,833	582,833	582,833
Mean Agree	0.654	0.654	0.654	0.654	0.654	0.654
Joint p-value						0.916

Notes: This table shows the results of estimating Equation (2.1) using only those legislators with adjacent colleagues from a different European group. *Peer IG* takes a value of 1 if the peer who was part of an interest group is from a different party, and a value of 0 if no peer was part of an interest group. We denote as Joint p-value the test on the joint significance of the seating adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group. A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.22: Average effect of reverse revolving doors connections on vote coincidence by name distance

	(1) OLS Agree	(2) OLS Agree	(3) OLS Agree	(4) OLS Agree	(5) OLS Agree
Name Peers IG dist. 1	0.0058	0.0051	0.0049	0.0041	0.0039
	(0.0049)	(0.0048)	(0.0048)	(0.0047)	(0.0047)
Name Peers IG * Relevant dist. 1	0.0071*	0.0071*	0.0071*	0.0073*	0.0073*
	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)
Name Peers IG dist. 2	0.0027	0.0025	0.0013	0.0005	-0.0001
	(0.0047)	(0.0046)	(0.0047)	(0.0046)	(0.0046)
Name Peers IG * Relevant dist. 2	0.0078**	0.0073*	0.0072*	0.0072*	0.0076**
	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0038)
Name Peers IG dist. 3		0.0050	0.0055	0.0041	0.0033
		(0.0042)	(0.0042)	(0.0042)	(0.0042)
Name Peers IG * Relevant dist. 3		0.0076**	0.0068*	0.0065*	0.0067*
		(0.0036)	(0.0036)	(0.0036)	(0.0036)
Name Peers IG dist. 4			-0.0001	-0.0005	-0.0011
			(0.0050)	(0.0050)	(0.0050)
Name Peers IG * Relevant dist. 4			0.0073*	0.0077*	0.0078*
			(0.0042)	(0.0042)	(0.0041)
Name Peers IG dist. 5				0.0019	0.0014
				(0.0040)	(0.0040)
Name Peers IG * Relevant dist. 5				0.0017	0.0014
				(0.0037)	(0.0037)
Name Peers IG dist. 6					0.0002
					(0.0038)
Name Peers IG * Relevant dist. 6					0.0037
					(0.0038)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes
Observations	6,767,838	6,742,171	6,718,746	6,704,043	6,724,801
Mean Agree	0.707	0.707	0.706	0.706	0.705
p-value, coefficients zero	0.0202	0.0108	0.00671	0.0116	0.0129
p-value, coefficient dist. 1 equal to dist. 2	0.764	0.770	0.663	0.642	0.641
p-value, coefficient dist. 1 equal to dist. 3	-	0.957	0.980	0.909	0.867
p-value, coefficient dist. 1 equal to dist. 4	-	-	0.603	0.645	0.620
p-value, coefficient dist. 1 equal to dist. 5	-	-	-	0.302	0.261
p-value, coefficient dist. 1 equal to dist. 6	-	-	-	-	0.317

Notes: This table shows the results of estimating how name adjacency to legislators with interest group background affect their probability of voting alike at different distance levels. A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.23: Average effect of reverse revolving doors connections on vote coincidence - Row level analysis

	(1) OLS Agree	(2) OLS Agree	(3) OLS Agree	(4) OLS Agree
Num. IG members	0.0835**	0.0509**	0.0511**	0.0396
	(0.0339)	(0.0225)	(0.0227)	(0.0243)
Num. IG members * Relevant				0.0737***
				(0.0209)
EPG x Term FEs	No	Yes	Yes	Yes
Sessions since term started FEs	No	Yes	Yes	Yes
Procedure type FEs	No	No	Yes	Yes
Vote subject FEs	No	No	Yes	Yes
MEP controls	No	No	No	Yes
Observations	638,461	638,455	638,455	638,455
Mean Agree	0.704	0.704	0.704	0.704
Joint p-value				0.000249

Notes: This table shows the results of estimating Equation (2.1) collapsed at the row (by aisle) level. It tests whether having more legislators with previous experience in Interest Groups in a given chamber row affects the row voting agreement. We denote as Joint p-value the test on the joint significance of the number of legislators with previous interest group experience, and the number of those for whom the topic is relevant. We control by row size and by a comprehensive set of controls collapsed at the row level. See Appendix 1.A for further information on the controls included. Standard errors are clustered both at the plenary session and at the row-by-aisle level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.24: Average effect of reverse revolving doors connections on vote coincidence using different clustering levels

	(1) OLS Agree	(2) OLS Agree	(3) OLS Agree	(4) OLS Agree
Name Peers IG	0.0059	0.0059	0.0059	0.0059*
	(0.0050)	(0.0050)	(0.0047)	(0.0034)
Name Peers (IG * Relevant)	0.0073*	0.0074*	0.0073*	0.0073**
	(0.0039)	(0.0042)	(0.0041)	(0.0035)
EPG x Term FEs	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes
Observations	6,770,336	6,770,336	6,770,336	6,770,336
Mean of Dependent Var.	0.707	0.707	0.707	0.707
Joint p-value	0.0239	0.0453	0.0360	0.00602

Notes: This table shows the results of estimating Equation (2.1) using different clustering levels. All columns mimic Column 6 in Table 1.3, with differences in the clustering level, i) Column 1 clusters at the legislator level, ii) Column 2 clusters at the legislator and plenary session levels, iii) Column 3 clusters at the row and plenary session level, and iv) Column 4 clusters at the EPG and plenary session level. We denote as Joint p-value the test on the joint significance of the name adjacency to a legislator with previous interest group, and when the topic is relevant for such interest group. A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.25: Average effect of reverse revolving doors connections on vote coincidence by drafting committee membership

	Drafting Member			No Drafting Member		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
	Agree	Agree	Agree	Agree	Agree	Agree
Name Peers IG	-0.0027	-0.0036		0.0066	0.0059	
	(0.0173)	(0.0176)		(0.0049)	(0.0050)	
Name Peers (IG * Relevant)		0.0086			0.0073*	
		(0.0223)			(0.0039)	
Peers IG			-0.0048			0.0080
			(0.0256)			(0.0066)
Peers (IG * Relevant)			0.0110			0.0091*
			(0.0281)			(0.0049)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,754	40,754	40,754	6,729,546	6,729,546	6,729,546
Mean of Dependent Var.	0.711	0.711	0.711	0.707	0.707	0.707
Joint p-value		0.845	0.858		0.0242	0.0261
F-stat 1			322.9			1056
F-stat 2			228.5			1300

Notes: This table shows the results of estimating Equation (2.1) using only those legislators that are part of the committee in charge of drafting the motion voted on and those who are not. We denote as Joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.26: Average effect of reverse revolving doors connections on vote coincidence including peer expertise

	(1) OLS Agree	(2) OLS Agree	(3) OLS Agree	(4) OLS Agree	(5) OLS Agree	(6) OLS Agree
Name Peers Expert	0.0035	0.0032	0.0026	0.0028	0.0026	0.0026
	(0.0024)	(0.0024)	(0.0031)	(0.0024)	(0.0031)	(0.0031)
Name Peers IG		0.0067	0.0061	0.0060	0.0058	0.0058
		(0.0049)	(0.0053)	(0.0050)	(0.0053)	(0.0053)
Name Peers (IG * Expert)			0.0022		0.0007	0.0004
			(0.0059)		(0.0058)	(0.0059)
Name Peers (IG * Relevant)				0.0074*	0.0073*	0.0065
				(0.0039)	(0.0039)	(0.0050)
Name Peers (IG * Expert * Relevant)						0.0092
						(0.0304)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,770,336	6,770,336	6,770,336	6,770,336	6,770,336	6,770,336
Mean Agree	0.707	0.707	0.707	0.707	0.707	0.707
Joint p-value			0.0530	0.0236	0.00984	0.359

Notes: This table shows the results of estimating Equation (2.1) adding as regressors whether name adjacent legislators have expertise on the motion voted on, as well as the interactions with $NamePeers\ IG$ and $NamePeers\ IG\ *\ Relevant$. We denote as Joint p-value the test on the joint significance of all displayed variables. A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.27: Average effect of reverse revolving doors connections on vote coincidence by voting stage

	Amendments			Final votes		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
	Agree	Agree	Agree	Agree	Agree	Agree
Name Peers IG	0.0056	0.0048		0.0096*	0.0091*	
	(0.0052)	(0.0052)		(0.0054)	(0.0055)	
Name Peers (IG * Relevant)		0.0081*			0.0061**	
		(0.0046)			(0.0030)	
Peers IG			0.0065			0.0122*
			(0.0069)			(0.0073)
Peers (IG * Relevant)			0.0102*			0.0075**
			(0.0057)			(0.0037)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,220,263	5,220,263	5,220,263	1,550,073	1,550,073	1,550,073
Mean Agree	0.703	0.703	0.703	0.722	0.722	0.722
Joint p-value		0.0466	0.0495		0.00497	0.00573
F-stat 1			1034			1048
F-stat 2			1180			1756

Notes: This table shows the results of estimating Equation (2.1) using only amendment and final votes. We denote as Joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.28: Average effect of reverse revolving doors connections on vote correction and intention

	(1) OLS Correction	(2) OLS Correction	(3) 2SLS Correction	(4) OLS Intention	(5) OLS Intention	(6) 2SLS Intention
Name Peers IG	-0.0000	-0.0000		-0.0013	-0.0013	
	(0.0003)	(0.0003)		(0.0018)	(0.0018)	
Name Peers (IG * Relevant)		-0.0003*			0.0009	
		(0.0002)			(0.0009)	
Peers IG			-0.0000			-0.0018
			(0.0004)			(0.0025)
Peers (IG * Relevant)			-0.0004*			0.0011
			(0.0002)			(0.0012)
EPG x Term FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,881,658	5,881,658	5,881,658	888,675	888,675	888,675
Mean Agree	0.0023	0.0023	0.0023	0.0051	0.0051	0.0051
Joint p-value		0.290	0.304		0.841	0.810
F-stat 1			1020			771.4
F-stat 2			1236			860.1

Notes: This table shows the results of estimating Equation (2.1). Columns 1, 2 and 3 use the sample of votes in which legislators actually cast a vote, and test whether they correct it afterwards, denoted by *Correction*. Columns 4, 5 and 6 use the sample of votes in which legislators did not go to vote and test whether they announced what was their voting intention, denoted by *Intention*. We denote as Joint p-value the test on the joint significance of the adjacency to a legislator with previous experience in an interest group, and when the topic is relevant for such interest group (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.29: Average effect of reverse revolving doors connections on vote coincidence persistence by plenary sessions

	(1) OLS Agree	(2) OLS Agree	(3) OLS Agree	(4) 2SLS Agree
Name Peers IG	0.0059	0.0043	0.0034	
	(0.0050)	(0.0069)	(0.0068)	
Name Peers (IG * Relevant)	0.0073*	0.0073*	0.0164**	
	(0.0039)	(0.0039)	(0.0064)	
Sessions name adjacent	-0.0000	-0.0000	-0.0000	
	(0.0001)	(0.0001)	(0.0001)	
Name Peers IG * Sessions name adjacent		0.0001	0.0001	
		(0.0002)	(0.0002)	
Name Peers (IG * Relevant) * Sessions name adjacent			-0.0003	
			(0.0002)	
Peers IG				0.0048
				(0.0094)
Peers (IG * Relevant)				0.0225**
				(0.0089)
Sessions seat adjacent				-0.0001
				(0.0002)
Peers IG * Sessions seat adjacent				0.0002
				(0.0004)
Peers (IG * Relevant) * Sessions seat adjacent				-0.0006*
				(0.0004)
EPG x Term FEs	Yes	Yes	Yes	Yes
Sessions since term started FEs	Yes	Yes	Yes	Yes
Procedure type FEs	Yes	Yes	Yes	Yes
Vote subject FEs	Yes	Yes	Yes	Yes
Name controls	Yes	Yes	Yes	Yes
Focal MEP controls	Yes	Yes	Yes	Yes
Peers controls	Yes	Yes	Yes	Yes
Observations	6,770,336	6,770,336	6,770,336	6,770,336
Mean Agree	0.707	0.707	0.707	0.707
Joint p-value		0.131	0.0322	0.0322
F-stat (KP)				188

Notes: This table shows the results of estimating Equation (2.1) adding as regressors the number of previous plenary sessions in which each legislator has been assigned to sit adjacent to the same two other legislators, as well as the interactions with *Peers IG* and *Peers IG* $*$ *Relevant*, and their correspondent instruments. We denote as Joint p-value the test on the joint significance of all the variables displayed in the table (both at the surname and seating level). A comprehensive set of controls at the focal and peer legislators is used in the analysis. See Appendix 1.A for further information on the controls included. The reported F Statistics has been calculated following Kleibergen and Paap (2006). Standard errors are clustered at legislator level. *** p<0.01, ** p<0.05, * p<0.1.

Chapter 2

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

joint with Agnès Charpin[1]

2.1 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 with women overtaking 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,

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however, the literature has turned to new classes of explanations for these differences.[2] 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 the search and matching frictions existent in the job market. This myriad of confounding factors resulting into the observed 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 that by design shuts down the immediate demand-side factors and frictions present in other regular job markets. It allows us to focus on the role of job seekers' preferences for specific job characteristics, such as its expected earnings, work place amenities, and location. In particular, we exploit the French allocation mechanism of medical students to residency positions and analyse their occupational choices using both administrative and collected survey data. The labour market decisions made in this context are akin to those made in one-sided matching job market by highly skilled individuals which, by design, is exempt from demand-side preferences as well as search and matching frictions, and that additionally allows the researcher to observe each individual's choice set.

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 Examinations[3] or NRE) and are solely ranked according to their 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 through 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 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

[2]See 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.

[3]*Épreuves classantes nationales.*

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.[4] 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; Reuben, Sapienza and Zingales, 2015; Reuben, Wiswall and Zafar, 2017), differences in preferences for certain workplace

[4]See 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.

amenities (e.g. Lordan and Pischke, 2016; Cortes and Pan, 2017; Fluchtmann et al., 2020; Fortin, 2008; Wiswall and Zafar, 2018; 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,[5] 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 2.2 presents the setting under study and our different data sources. Sections 2.3 and 2.4 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 **??** and **??** 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,

[5]To 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 under-perform relative to men in competitive environments, and that the gender composition of the environment matters.

section 2.7 concludes.

2.2 Institutional Setting and Data

2.2.1 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.[6] The next two years of the curriculum are devoted to developing a wide and general set of skills. The forth, 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.[7] 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

[6]This 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.

[7]This usually occurs before the national ranking is made public.

place at that moment.[8]

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 preferences that candidates introduced during the simulation phase.[9] 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.[10]

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.[11] At the end of their specialisation, all students must submit a thesis to be allowed to practice as physicians.

2.2.2 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

[8]The 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.

[9]If 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.

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

[11]Under 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).

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;[12] *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 specialties for the years 2004 to 2009.[13] Second, we focus on the individuals who are allocated to a residency position.[14] 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 2.1 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).[15]

Figure 2.1 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

[12]The 26 subdivisions of continental France are shown in Figure 2.12 of the Appendix. There are two additional subdivisions in overseas France: Antilles-Guyane and Océan Indien.

[13]The 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.

[14]Each 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.

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

Table 2.1: Descriptive statistics on the NRE between 2010 and 2021.

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

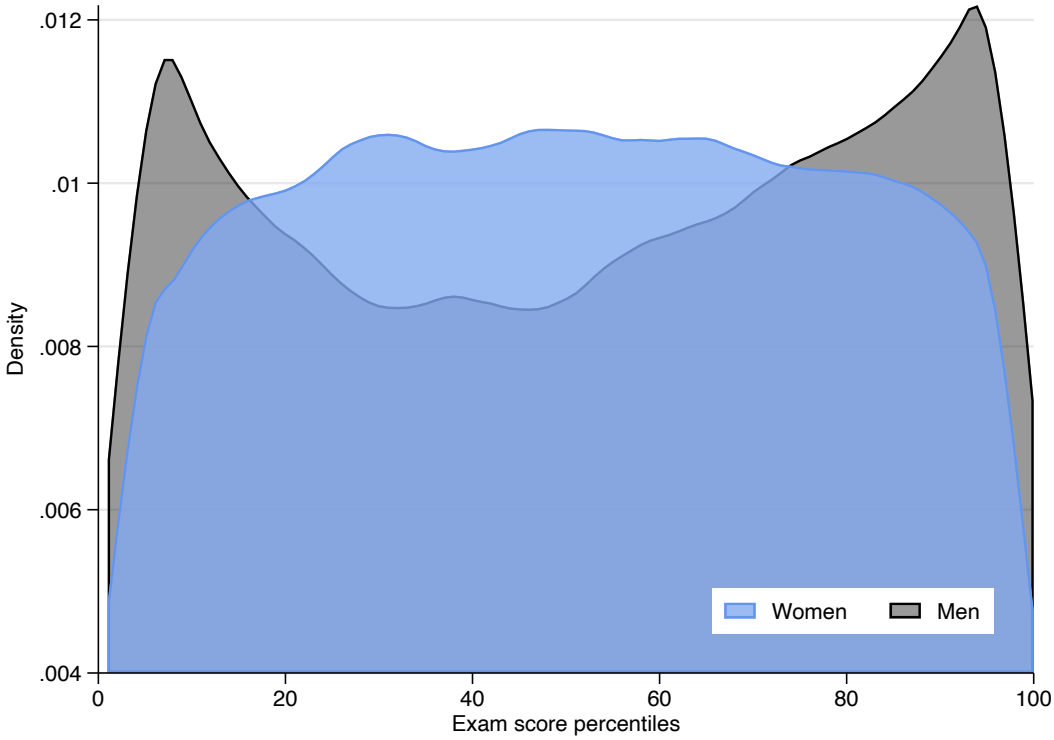
Notes: This table reports some descriptive statistics on the National Ranking Examinations between 2010 and 2021. *Nb vacancies* and *Nb takers* respectively report the number of vacancies that are offered on a given year on average, and the number of candidates taking the exam on a given year on average. 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.

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).

2.2.3 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,

Figure 2.1: 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.

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.

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. 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".[16] 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 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.[17] We merge this data to the NRE file using information on specialty.

Figure 2.2 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.

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 a maximum of 48 hours and participate in maximum one night shift per week.[18] 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.

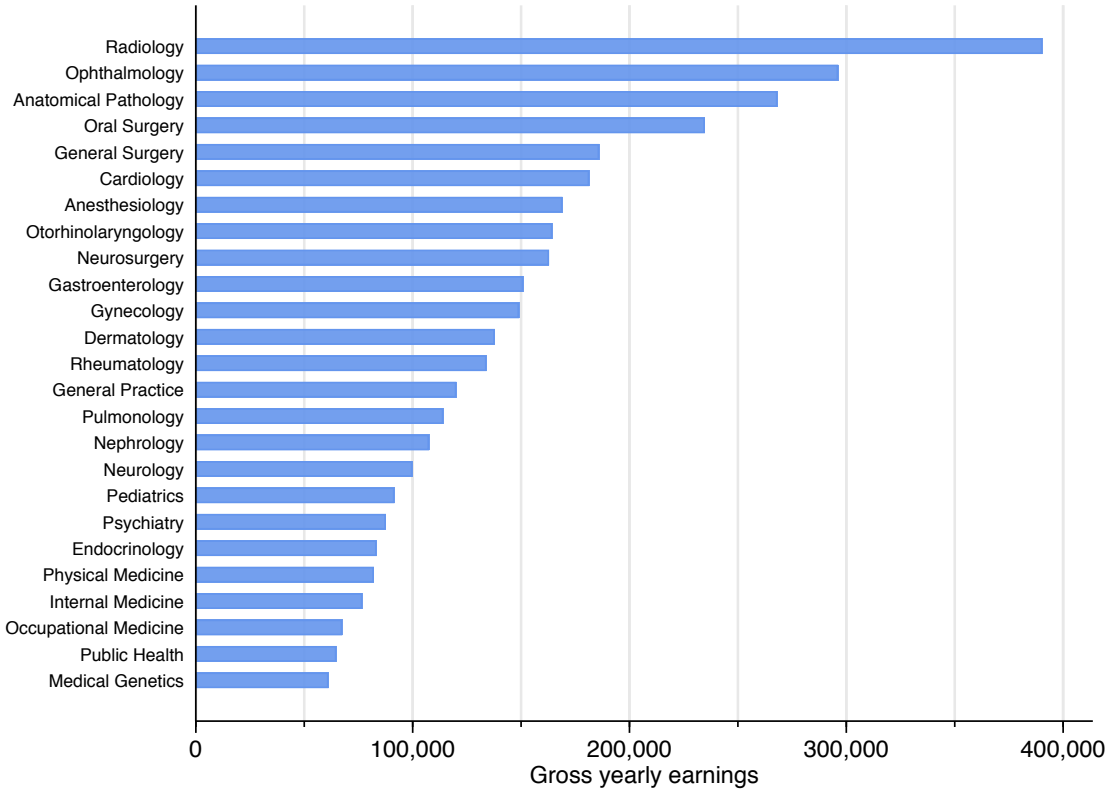
Figure 2.3 plots the average number of hours worked in a week and the number of night shifts worked in a month by residents in each specialty. It highlights the variation that exists in these two dimensions across specialties: residents in neurosurgery and general

[16] Article 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."

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

[18] Decree number 2015-225 from February 26, 2015.

Figure 2.2: Expected yearly earnings by specialty.



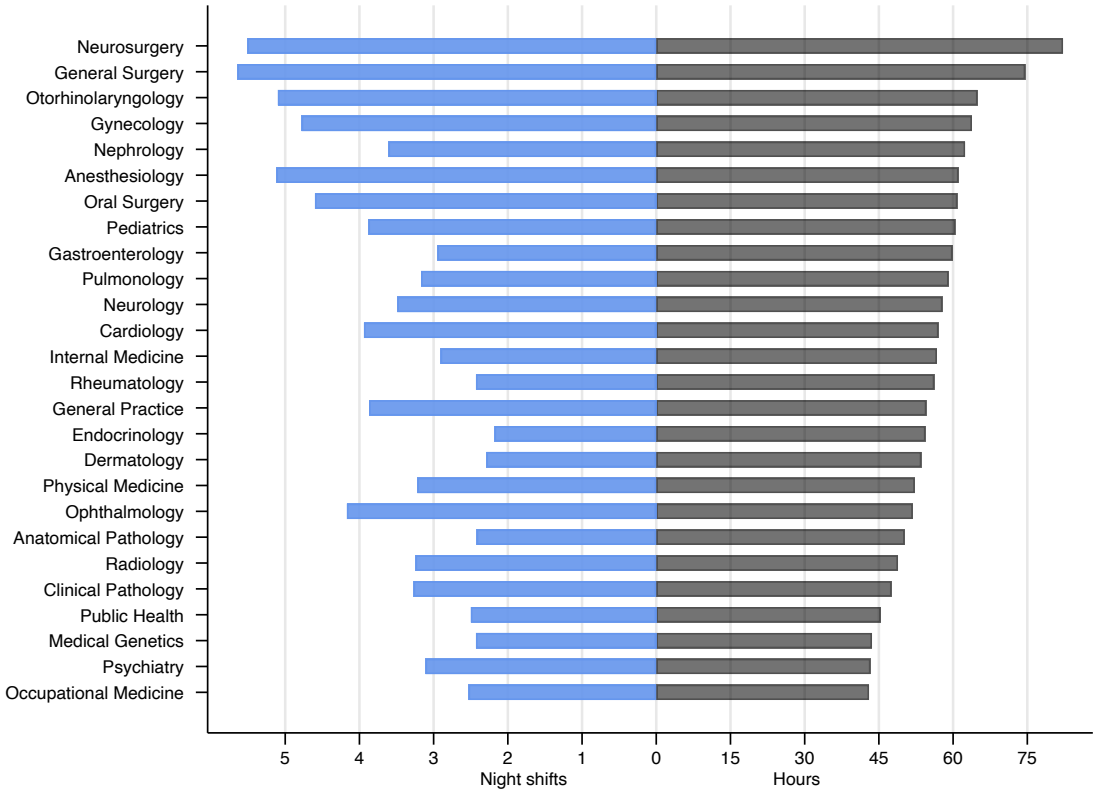
Notes: This figure shows the yearly gross earnings that physicians can expect to earn in each specialty on average. This measure combines aggregated data on the earnings of private physicians provided by the CNAMTS and hospital salary grids collected from the Official Journal of the French Republic,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

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.

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

Figure 2.3: 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*).

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.[19] Following Cortes and Pan (2017), we create four composite indices to characterise the different medical specialties, as described in Table 2.5 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.

[19]Specifically, we fail to match cardiology, hematology, legal medicine, nephrology, oncology, and otorhinolaryngology.

2.3 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.

2.3.1 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 2.B.2.

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

$$y_i = \beta female_i + \gamma_{c(i)} + \epsilon_i \tag{2.1}$$

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 2.13 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 2.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 (2.1) at different positions of the exam score distribution, and report the results in Figure 2.14 in Appendix 2.A.

2.3.2 Results

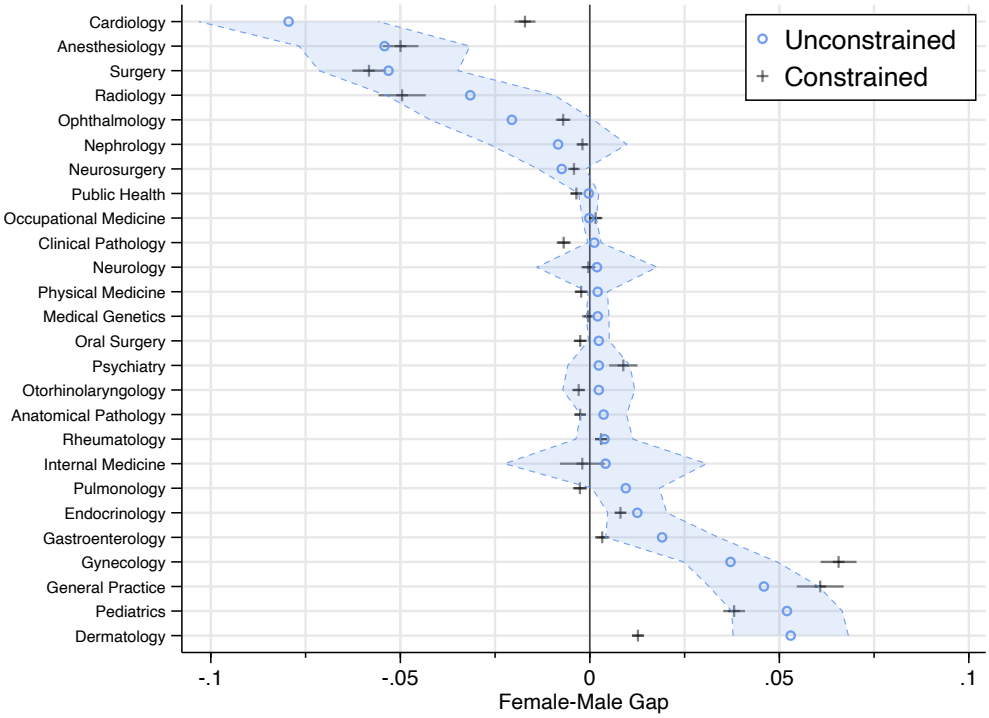
Figure 2.4 plots gender differences in the propensity to self-select into specialties, separately for the unconstrained and constrained groups of candidates. Precisely, each row reports the coefficient $\hat{\beta}$ and its 95% confidence interval estimated from equation (2.1) using an indicator variable 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 2.4 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 2.4: Gender differences in revealed preferences for medical specialties.



Notes: This figure plots the coefficients $\hat{\beta}$ and 95% confidence intervals estimated from equation (2.1), 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 2.14 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.[20]

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.

2.4 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.

2.4.1 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 (2.1) 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 2.5. We find that women are on average less likely

[20] The 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.

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 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.[21]

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.

2.4.2 Gender Differences in Preferences for Non-Monetary Attributes

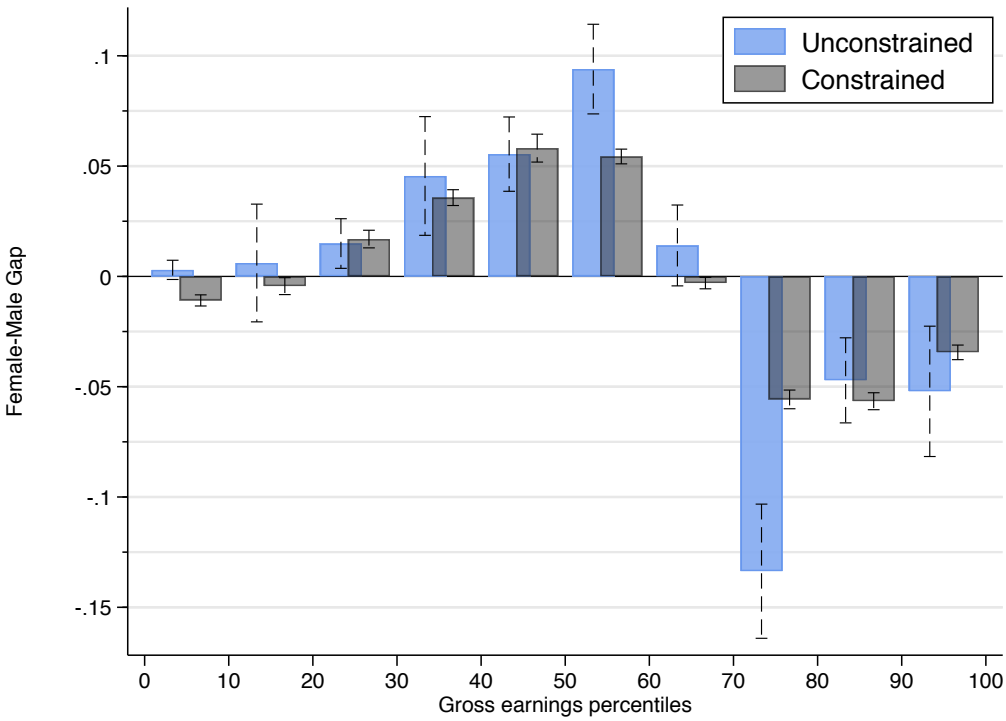
We then turn to estimating the gender gaps in preferences for the non-pecuniary dimensions of the occupation decision. We split the distribution of hours worked and night shifts performed in quartiles, and then proceed as in section 2.4.1. To do so, for each occupational characteristic, we define four indicator variables taking value 1 if the characteristic under study (hours worked, number of night shifts) observed in the specialty chosen by individual i belongs to the corresponding quartile of its distribution and to 0 otherwise. We then estimate equation (2.1) 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 2.6 and 2.7.

Figure 2.6 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 2.7 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

[21] A very similar pattern of results is found when using non-hospital gross earnings instead of overall gross earnings as reported in Figure 2.15 in the Appendix.

Figure 2.5: Gender gap in selection on gross expected earnings.

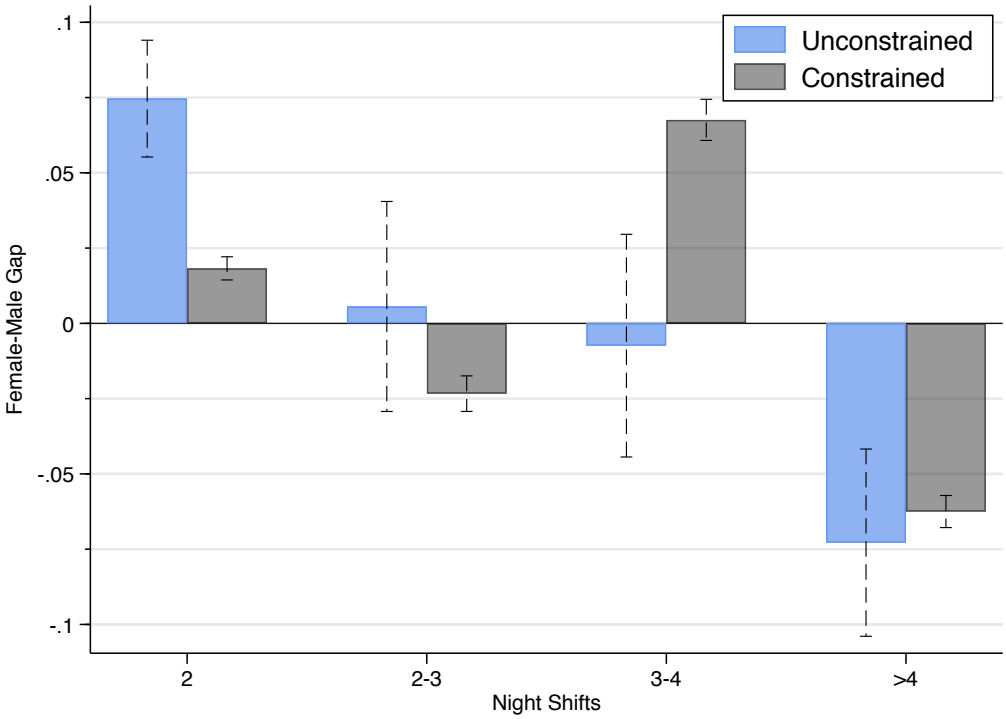


Notes: This figure shows the gender gaps in the probability of self-selecting into a residency position that falls in each of the deciles of the gross earnings distribution. Negative (positive) values indicate that women are less (more) likely to self-select into specialties with higher expected earnings 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.

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.

Finally, we estimate (2.1) using the occupational characteristic under study as defined in Table 2.5 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 2.8. 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

Figure 2.6: Gender gap in selection on night shifts.



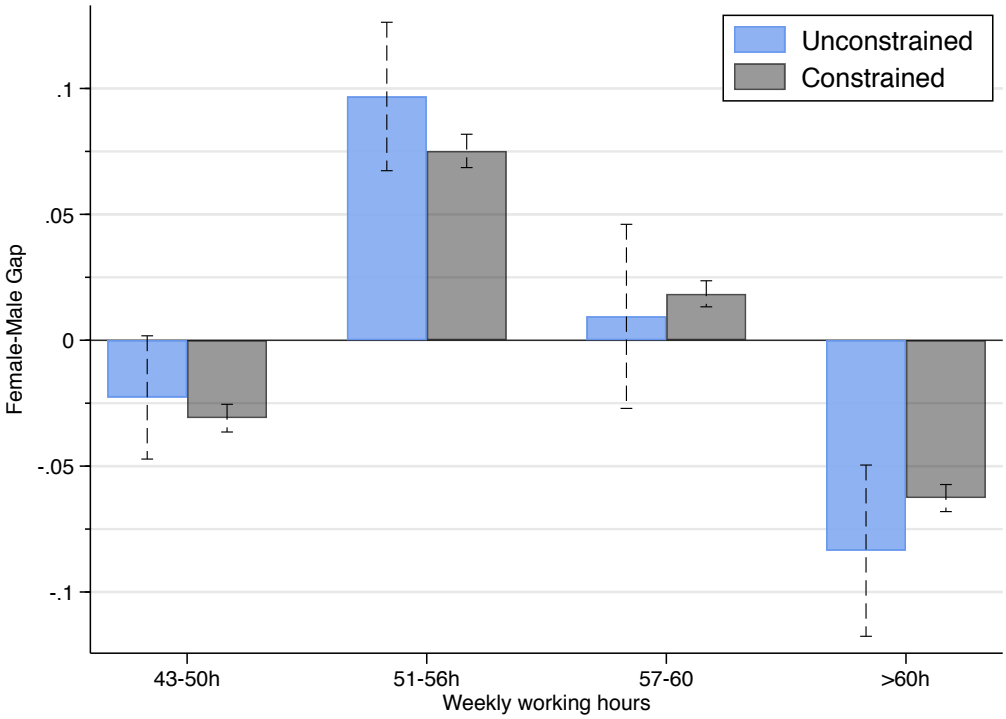
Notes: This figure plots gender gaps in the probability of females selecting a specialty that falls in each quartile of the monthly night shifts distribution, separately for the so called unconstrained and constrained individuals. Negative (positive) values indicate that, on average, women are less (more) 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.

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.

These results show that preferences for certain job characteristics play an important role in explaining gender occupational segregation: even when facing 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

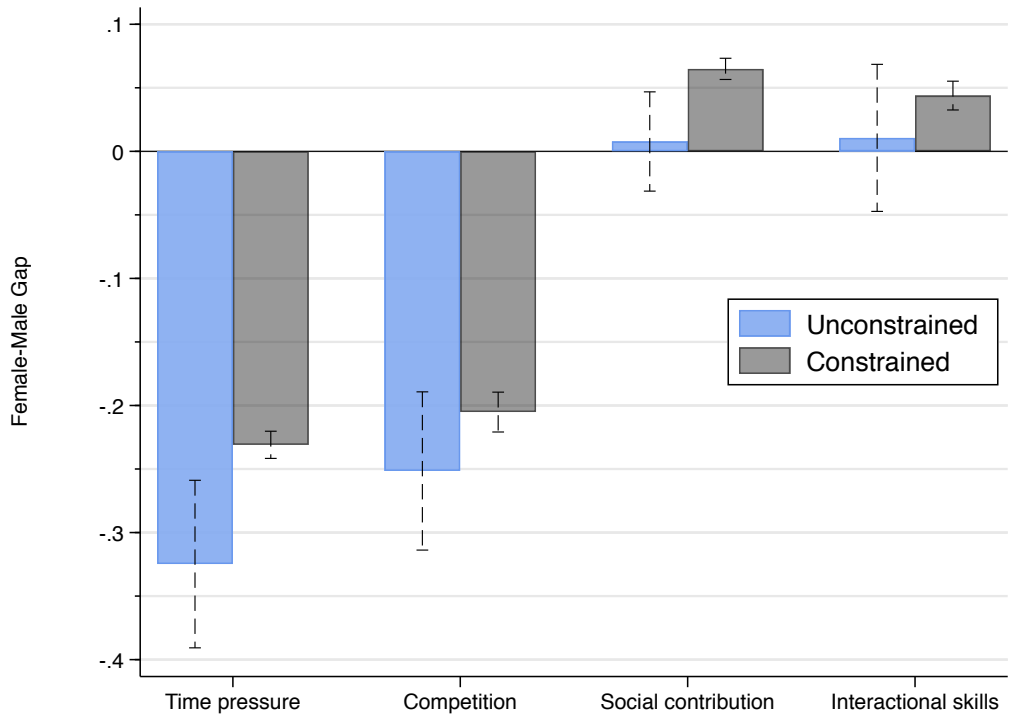
Figure 2.7: Gender gap selection on working hours.



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 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.

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.

Figure 2.8: 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.

2.5 Survey to Medical Students

So far, we have shown how gender differences in medical specialty choices relate to the gender earnings gap and to other relevant job characteristics in the medical profession. In order to obtain evidence on the reasons behind these different choices for medical occupations we administered an online survey on a sample of prospective NRE candidates over a four-week period in May 2022. The recruitment of medical students was performed under the MEDSPE research project headed by Professor Magali Dumontet and financed by the French National Research Agency (ANR JCJC).[22] In the context of another survey, the MEDSPE research team invited 8,056 of the 9,083 students who took the 2022 national practice exams (*Epreuves Classantes Nationales préparatoires* or NREp) that was held on March 21, 2022.[23] The ECNp are held on a national digital evaluation platform known

[22]We are very grateful to Magali Dumontet and Noémi Berlin for granting us access to a sample of their survey respondents and for sharing relevant information on them.

[23]The difference between the number of ECNp participants and the number of students that were contacted to take part in the first survey is due to the early extraction date of the contact details by the

as SIDES that also offers materials to prepare for the NRE.[24] The first survey within the MEDSPE project was administered between March 8 and March 20, 2022 and gathered 3,525 respondents. At the end of the first survey, 2,588 respondents gave their consent to be contacted again for follow-up surveys, and 1,352 of them took part in our survey. Table 2.2 summarises the descriptive characteristics that are jointly available for the two survey samples and for the NREp and NRE samples. Both surveys received an acceptable response rate, 43.8 and 52.2 percent respectively, with female students being more likely to participate in both. We also have had a higher response rate from students obtaining a higher score at the 2022 NRE. Finally both surveys provide a satisfactory geographic coverage, with similar regional distributions across groups.

Table 2.2: Students characteristics across groups

	1st survey			2nd survey		
	Contacted	Respondents	National Mock	Contacted	Respondents	National Exam
Females	5026 (62.5)	2384 (67.6)	5642 (62.2)	1755 (67.8)	945 (68.4)	5559 (59.9)
Males	3015 (37.5)	1141 (32.4)	3429 (37.8)	833 (32.2)	437 (31.6)	3375 (36.4)
National Exam Rank						
Take-up rate	97.2	98.2	96.9	98.3	98.5	100.0
1st quartile	26.1	27.3	25.2	27.7	29.3	25.0
2nd quartile	22.5	21.9	23.3	21.4	20.0	25.0
3rd quartile	21.3	19.8	22.5	19.5	17.4	25.0
4th quartile	23.6	20.3	25.1	20.1	18.6	25.0
Contact and response rates	88.7%	43.8%		73.4%	53.4%	
Total	8043	3525	9072	2588	1382	9284

Notes: Notes: This table shows the total number and shares of students belonging to different groups.

The data was collected through Qualtrics, a web-based survey tool. The survey took approximately 25 minutes to complete, and respondents who completed the survey were offered to take part in a lottery to win one of 17 prizes of a total value of 1,462 euros.[25]

In addition to questions about demographics and family background, the survey consisted of several sections. We started by asking respondents about their preferences in terms of residency positions and their expected performance at the NRE. We also tested their knowledge of the working conditions in their preferred specialty as well as one female-dominated and one male-dominated specialty. The main section of the survey consisted in a discrete choice experiment with hypothetical job choices, as described in the next subsection. We complemented the information collected through the hypothetical job choices by asking respondents how important a series of characteristics were in their residency position choice. Finally, we asked respondents about their experiences and expectations regarding gender-based discrimination and elicited their beliefs about gender norms.

research team.

[24]SIDES stands for *Système Informatisé Distribué d'Évaluation en Santé.*

[25]We are very grateful to the EUI for funding the prizes through an Early Stage Research grant.

2.5.1 Respondents' Demographic Characteristics

Table 2.3 shows some demographics characteristics of our survey respondents. The average age for women in our sample is 24.3 years which is 4 months less than for men, and 99 percent them are French while 95 percent of men are. Similar rates of marital status are reported across genders. For both genders 65 percent of them report being single, around 30 percent being in a free union and the rest being married or in a civil partnership. Relevant gender difference in size are present when we look at the respondents' fertility plans. While 30 percent of women report wanting to have children in the next 5 years, only 22 percent of men want so. As expected virtually all respondent followed the scientific stream in the upper secondary school, and there is a higher share of women obtaining the highest honors. In terms of parental education, there is a higher share of females respondents who have parents with tertiary education compared to men. Finally, there are no relevant gender differences in the share of respondents who passed their first year of medicial school in their first attempt nor in the ranking of their GPA.

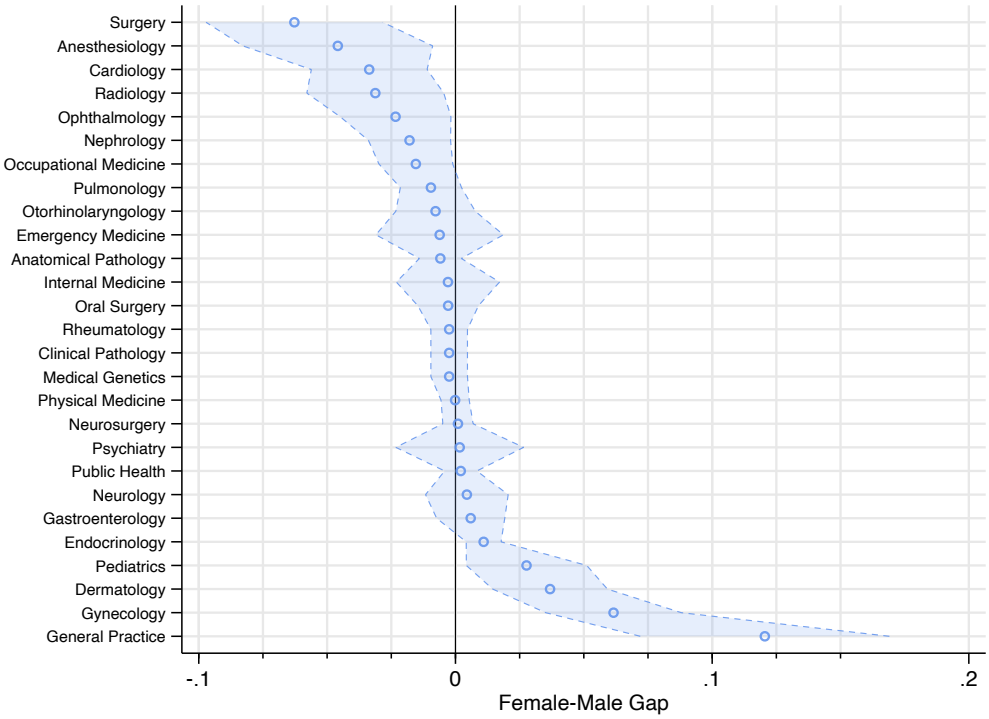
2.5.2 Survey general results

In this subsection, we examine gender differences in the preferred specialty elicited in the survey and on respondents exam performance expectations. Early in the survey, respondents provided us with their most preferred residency position (medical specialty and location). For this question we were after respondents' most preferred speciality and location regardless of their performance expectations in the upcoming national exam. These were elicited by instructing respondents to imagine that they had obtained an exam rank that allowed them to choose the position that they desired the most. Gender differences in the probability of reporting each specialty as the preferred one are presented in Figure 2.9. We find the same pattern of differences across genders in speciality selection as the one found when using the administrative data with the official choices. This should not be surprising as the allocation mechanism obtains truthful preference revealing.

Next, we show respondents' expected performance at the 2022 NRE. This was elicited by asking respondents to introduce the probability that their actual rank in the 2022 exam will fall into each of the presented intervals. The usage of subjective marginal probabilities creates the usual trade-off in survey design of obtaining more detailed answers at the expense of requiring the respondents to exert a higher effort to provide them. Since there were more than 9,000 students registered to take the 2022 NRE, we provided survey respondents with 19 intervals each comprising 500 subsequent ranks. We obtained each respondent expected exam score by adding up each interval median value and weighting it by the revealed marginal probability.

Figure 2.10 presents the density distribution of the expected exam score for each gender

Figure 2.9: Gender differences in stated preferences for medical specialties.



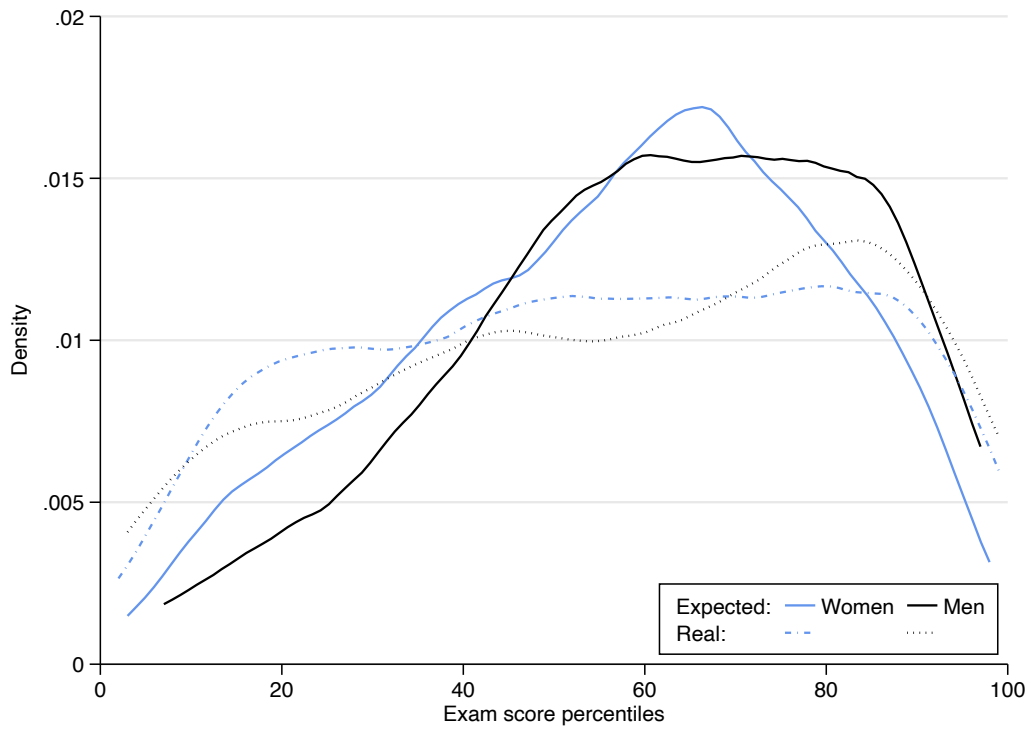
Notes: This figure replicates Figure 2.4 using individual responses to the following survey question: *"Imagine that the rank that you are about to get at the NRE allows you to pick* ***whichever position*** *you want. Which one would you choose?"*.

as well as that of the real score obtained later in the exam. Male respondents expect to achieve higher scores than women, a finding that is corroborated by the distribution of the real score. Female respondents seem to be more cautions when predicting their score since they end up in the upper part of the distribution more often than what they expect. Finally, in both cases the distribution of the expected score is more skewed to the left than that of the real score, which can imply a certain degree of over confidence in the exam performance by both genders.

2.6 Reasons for the Specialty Choice

In this section, we are interested in understanding which features drive the gender differences in occupational choices that have been highlighted in Section 2.3. We start by analysing the answers to questions about the reasons that led respondents to choose their preferred speciality. We then move to describing and estimating a discrete choice model using hypothetical job choices.

Figure 2.10: Expected and real exam score distributions by gender.



Notes: This figure plots the expected and real exam score distribution density for female and male respondents who took the NRE 2022.

2.6.1 Identifying Amenities for Medical Specialties

To understand what drives specialty choice, we start by focusing on the opinions provided by the respondents using free-text entries and multiple choice questions. Right after indicating their preferred residency position, respondents were asked to provide positive ('Pros') and negative ('Cons') features about that preferred specialty using a free-text type of response. This allows respondents to express themselves freely about the amenities they consider to be related to their *preferred* specialty and that matter the most to them. Moreover, it allows us to identify the sentiment of each amenity depending on whether it was mentioned in the 'Pros' or 'Cons' question.

We borrow four categories identified in Sockin (2021) which contain a total of 30 amenities, and adapt them to the healthcare sector in France.[26] In our case, the first category is related to pay and comprises two amenities about base salary and its progression. The second category relates to working conditions and contains the following 19 amenities: work-life balance, hours worked, work schedule, commuting, teleworking, location, autonomy/responsibility, respect/abuse, difficulty, requirements, stress, pace, safety,

[26]Sockin (2021) analyses positive and negative features of job reviews posted by workers on a labour market website. The author implements a topic modelling machine learning algorithm to identify latent amenities in the text using topic-specific anchor-words that help the algorithm's effectiveness in identifying topics that can be interpreted as specific amenities.

recognition, fun, culture, diversity/inclusion, leadership and change. The third category relates to human capital and includes amenities related to career concerns, promotions, skill development, on-the-job training, and the medical residency. The fourth and last category is interpersonal relationship with patients, managers, and coworkers.[27]

In order to identify amenities in the text written by each respondent, a set of words were assigned to each amenity and searched for in the free-text responses.[28] Table 2.4 presents the list of words that were assigned to each amenity.

Panel (a) of Figure 2.11 shows the incidence rate of each amenity as pros and cons associated with the respondents' preferred specialty, separately for men and women. The three most frequent amenities are the same in both positive and negative type of opinions and for both genders. The most discussed amenities in opinions with a positive sentiment about the preferred speciality are related to the relationship with the patient (40% for females and 22% for males), diversity and inclusion (23% and 18%), and the work schedule (12% and 10%). The latter was also the most discussed amenity in the negative aspects with (21% in both genders), followed by the relationship with the patient (12%), and the difficulty of the specialty (11% and 9%).

The fact that some amenities are mentioned both as pros and cons reveals the existence of individual heterogeneity in opinions about the amenities that encourage and dissuade selecting a specialty. Panel (b) of Figure 2.11 breaks the incidence of amenities into two groups depending on the gender that is more likely to choose the specialty as their preferred one. We select the gender dominated specialties using the results reported in Figures 2.4 and 2.9. Respondents who indicated that their preferred speciality is anesthesiology, cardiology, surgery, or radiology are grouped into the *male* dominated specialties, while those who reported preferring dermatology, GP, gynecology, or pediatrics are grouped into *female* dominated specialties.

This grouping allows us to highlight several interesting results. First, respondents who prefer a male-dominated specialty consider the relationship with the patient less as a positive feature than those who prefer a female dominated specialty. In both cases, women discussed that amenity more frequently than men. Second, the work schedule is mentioned as a negative aspect of the specialty much more often in male-dominated specialties than in female-dominated specialties, with women discussing it significantly more than men. Third, team work is more positively valued by those preferring a male-dominated speciality than those preferring a female-dominated specialty, with once again women declaring it more than men. Finally, while pay stands out as being a positive

[27]For the details about the reasons behind the selection of each amenity we refer to the references in Sockin (2021).

[28]Free-text responses were pre-processed by removing common stop words and lemmatising each word using the trained model for natural language recognition *fr_dep_news_trf* developed with the software library *spaCy*.

aspect for those respondents preferring a male-dominated specialty, it is a negative aspect for those preferring a female-dominated specialty.

These results are indeed supported by additional results using a more conventional question that asked respondents to select the most important factor in their specialty choice. Figure 2.16 shows the share of respondents who selected each of the predefined features. While not covering all the amenities used in the analysis of the free text entries, we still see how the three most important factor behind the speciality choice are work life balance, interest in the pathology and contact with patients. And indeed, the largest gender differences are found in the former and the latter features. Moreover, a higher share of men than women report the daily tasks and income levels as the most important factors behind their choices.

Analysing free text data with opinions about the 'pros' and 'cons' of the preferred speciality allows us to shed light on the differences across genders in preferences for the relevant amenities.

2.7 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.

Table 2.3: Respondents' Demographic Characterisitics

	(1)	(2)	(3)	(4)	(5)
	Women	Men	Diff.	p-value	Obs.
Age	24.31	24.65	-0.34***	0.005	1,299
French	0.99	0.95	0.04***	0.000	1,300
Marital status:					
Single	0.65	0.65	0.00	0.934	1,300
In a free union	0.29	0.31	-0.02	0.468	1,300
Married or in a civil partnership	0.05	0.03	0.02*	0.067	1,300
Divorced	0.00	0.01	-0.00	0.182	1,300
Fertility plans for the next 5 years:					
Wants children	0.30	0.22	0.09***	0.002	1,223
Does not want children	0.35	0.41	-0.06	0.042	1,223
Does not know	0.34	0.37	-0.03	0.372	1,223
Type of baccalauréat:					
Scientific	0.99	0.98	0.00	0.660	1,300
Non-scientific	0.01	0.02	-0.00	0.660	1,300
Baccalauréat honors:					
Highest honors or Very high honors	0.62	0.49	0.13***	0.000	1,298
High honors or Honors	0.36	0.47	-0.11***	0.000	1,298
No honors	0.02	0.04	-0.02**	0.023	1,298
Mother's education:					
High-school diploma or below	0.28	0.35	-0.07**	0.014	1,248
Bachelor's or equivalent	0.29	0.27	0.02	0.367	1,248
Master's or equivalent	0.32	0.26	0.06**	0.038	1,248
PhD or equivalent	0.11	0.12	-0.01	0.454	1,248
Father's education:					
High-school diploma or below	0.32	0.37	-0.05*	0.058	1,227
Bachelor's or equivalent	0.19	0.13	0.07***	0.004	1,227
Master's or equivalent	0.35	0.31	0.04	0.157	1,227
PhD or equivalent	0.14	0.19	-0.05**	0.018	1,227
Passed the first year of medical school:					
First attempt	0.48	0.46	0.02	0.427	1,258
Second attempt	0.51	0.51	-0.00	0.917	1,258
Other	0.01	0.03	-0.02**	0.010	1,258
Rank first year of medical school:					
Top 10%	0.20	0.23	-0.02	0.366	1,221
Top 10 to 25%	0.15	0.18	-0.03	0.261	1,221
Bottom 10%	0.12	0.12	0.00	0.846	1,221

Notes: This table reports some demographics characterisitcs about the sample of respondents. Reported p-values are from a two-sample t-test in which *** p<0.01, ** p<0.05, * p<0.1.

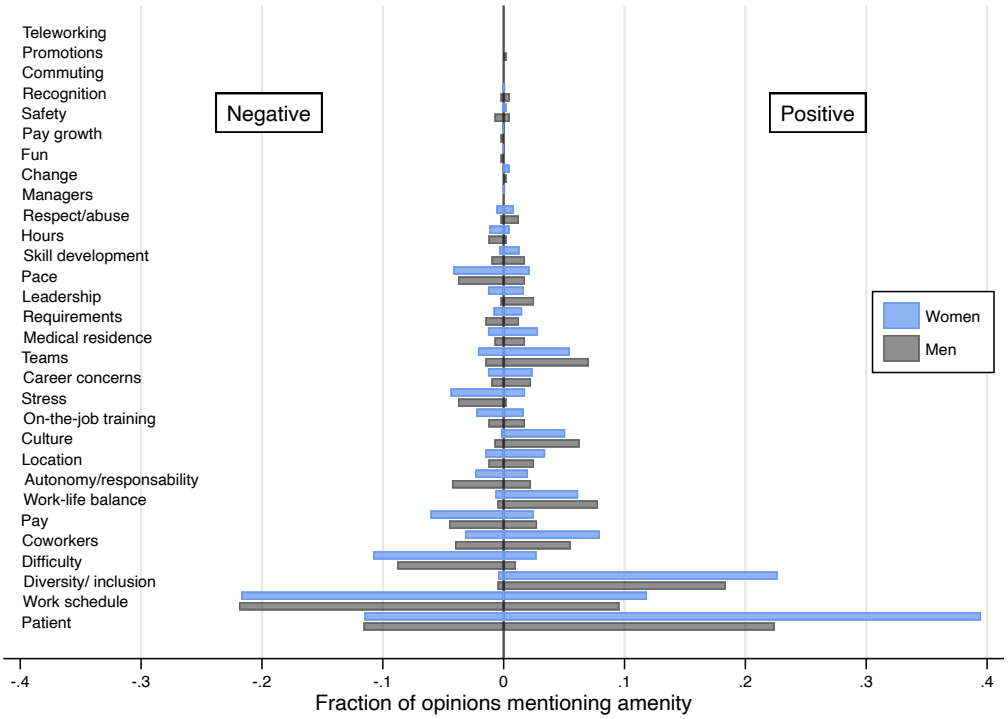
Table 2.4: Classification and identification of amenities

#	Category	Amenity	Searched words
1	Pay	Pay	pay, salary, base, base pay, money
2	Pay	Pay growth	raise, annual raise, salary increase, pay raise, raise base
3	Working conditions	Work-life balance	work life balance, work life, quality [of] life
4	Working conditions	Hours	hours, full time, part time
5	Working conditions	Work schedule	hours, night shift, shift, schedule, flex time
6	Working conditions	Commuting	commute, parking, bus, drive
7	Working conditions	Teleworking	telecommute, telework, work hom
8	Working conditions	Location	city, location, metro
9	Working conditions	Autonomy/responsability	autonomy, independence, responsability
10	Working conditions	Respect/abuse	respect, dignity, abuse, harass, hostile
11	Working conditions	Difficulty	challenge, difficult, easy
12	Working conditions	Requirements	require, requirement, mandatory, optional
13	Working conditions	Stress	stress, pressure, high stress, high pressure
14	Working conditions	Pace	pace, fast pace, speed
15	Working conditions	Safety	injury, dangerous, safety, conditions, workplace
16	Working conditions	Recognition	hard work, effort, reward, prestige
17	Working conditions	Fun	fun, boring, mundane, tedious
18	Working conditions	Culture	culture, values, environment, society, mission, human, human
19	Working conditions	Diversity/ inclusion	diversity, ethnic, multicultural, inclusive, lgbtq, inclusion, equality, diverse
20	Working conditions	Leadership	leadership, management
21	Working conditions	Change	change
22	Human capital	Career concerns	career, grow, improve, growth
23	Human capital	Promotions	promotion, promote, job title
24	Human capital	Skill development	develop, skill
25	Human capital	On-the-job training	train, training
26	Human capital	Medical residence	intern, internship
27	Relationships	Managers	boss, manager
28	Relationships	Coworkers	coworker, person, friend, family, colleague
29	Relationships	Teams	team, teamwork, collaborative
30	Relationships	Patient	patient, follow

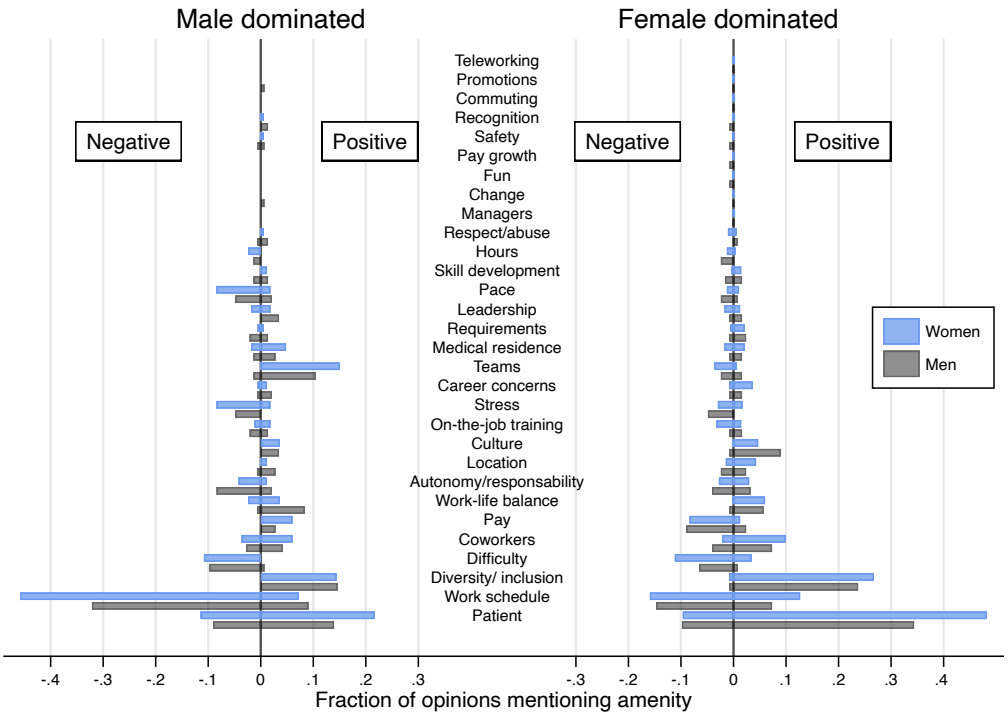
Notes: This table lists the words used to identify each of the amenities in the free-text responses.

Figure 2.11: Incidence of amenities in opinions about preferred specialty

(a) All opinions



(b) By the gender more likely to choose preferred specialty



Notes: This figure reports the fraction of times each amenity was identified in free-text opinions about the positive and negative features of their preferred speciality. Figure (a) shows incidence for all respondents while figure (b) splits them into two groups, male and female dominated, depending on which gender predominates in the preferred specialty. Words used to identify each amenity in the free-texts are reported in table 2.4. Texts were pre-processed by removing common french stop words and lemmatizing each of the remaining words using the trained model for natural language recognition *fr_dep_news_trf* developed with the software library *spaCy*. Amenities listed in ascending order according the the incidence rate of both types of opinions provided by females with a female dominated preferred specialty.

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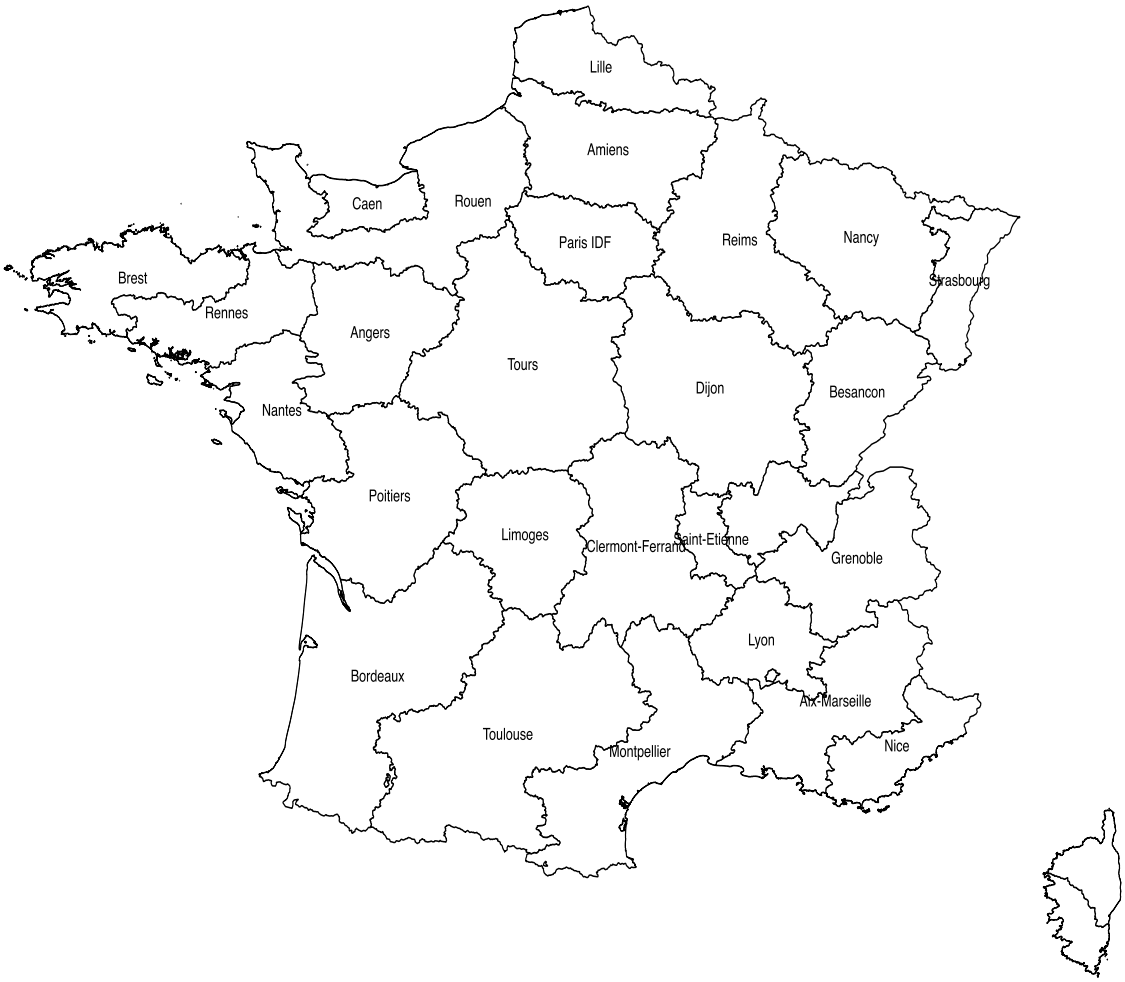
Appendix 2.A Supplementary Material

Figure 2.12: Subdivisions



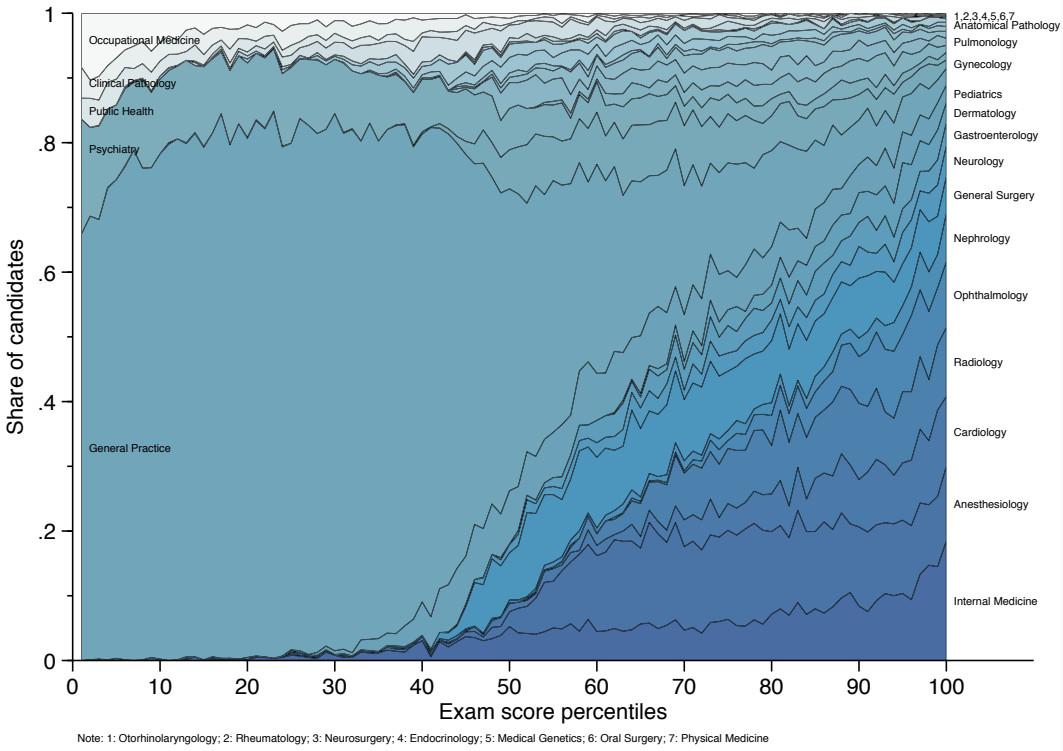
Notes: This figure shows the 26 subdivisions of continental France. Subdivisions are the geographical unit used at the NRE. There are two additional subdivisions in overseas France: Antilles-Guyane and Océan Indien.

Table 2.5: 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.
Social Contribution	Concern for others	"How important is concern for others to the performance of your current job?"	From not at all, to extremely.
	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.
Interactional Skills	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.
	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 2.13: 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 2.14: Gender gap in self-selection into specialties across the exam rank distribution.

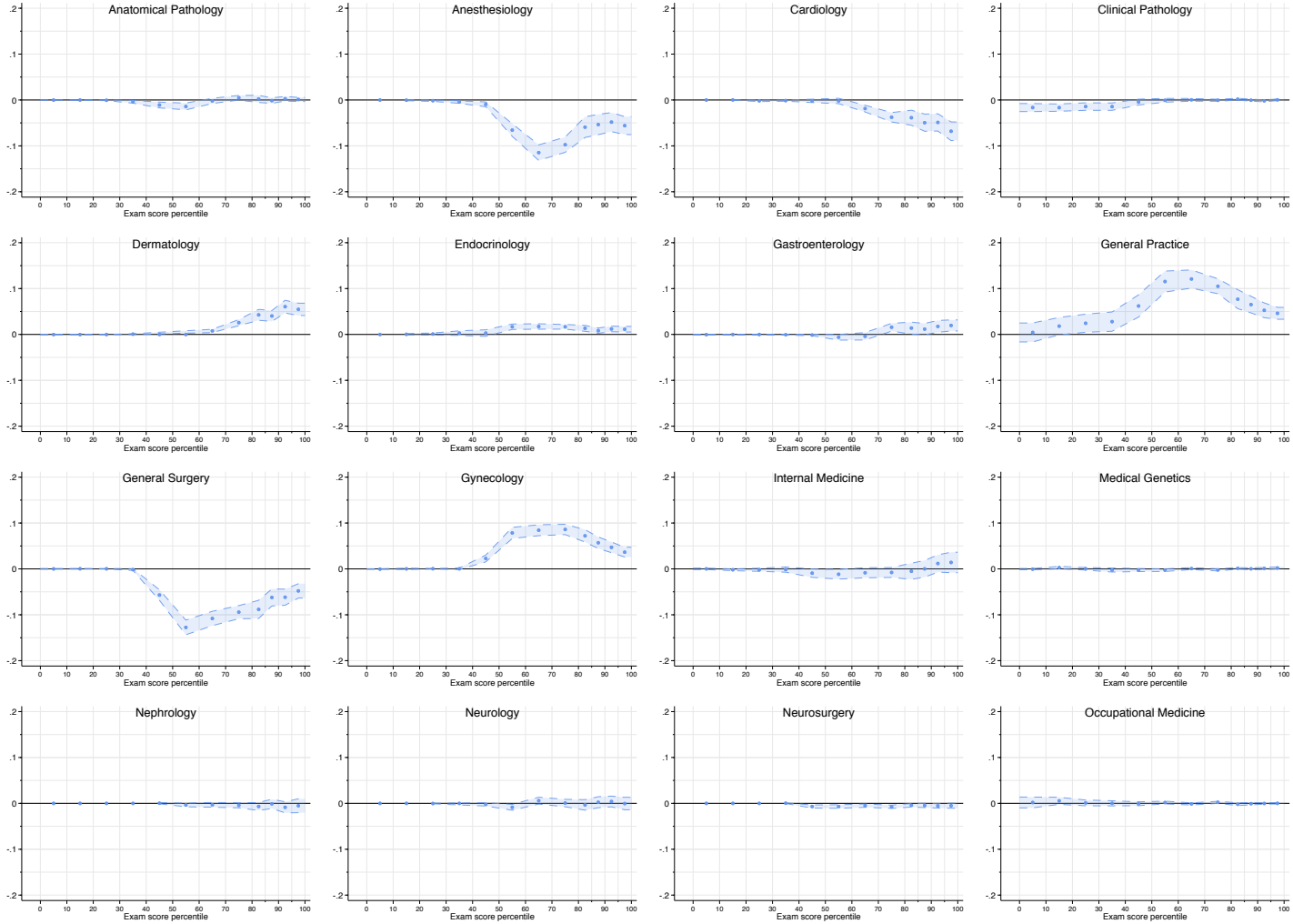
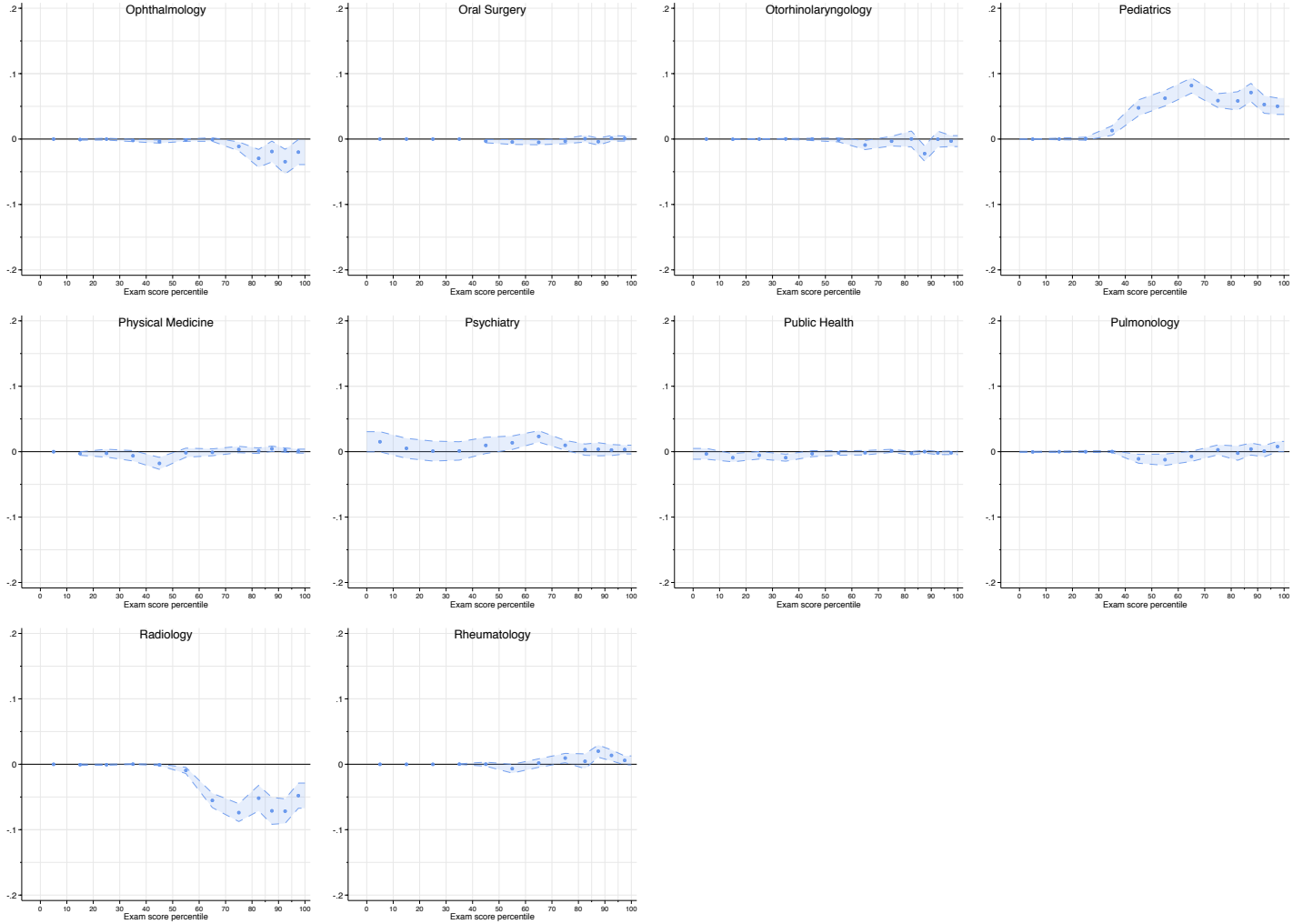
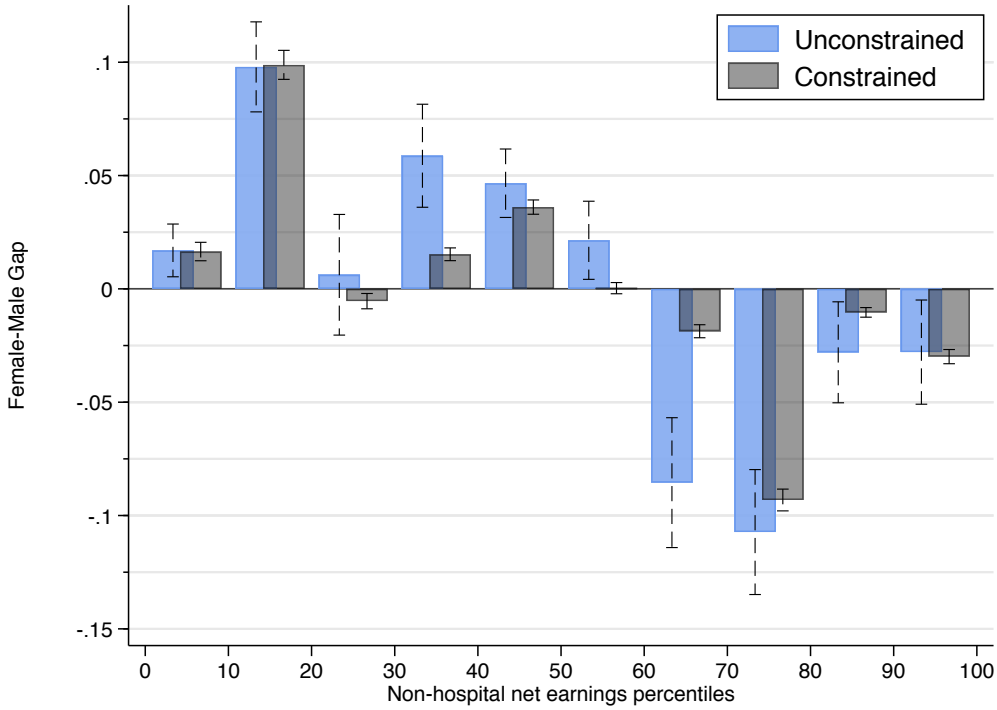


Figure 2.14 (cont.): Gender gap in self-selection into specialties across the exam rank distribution.



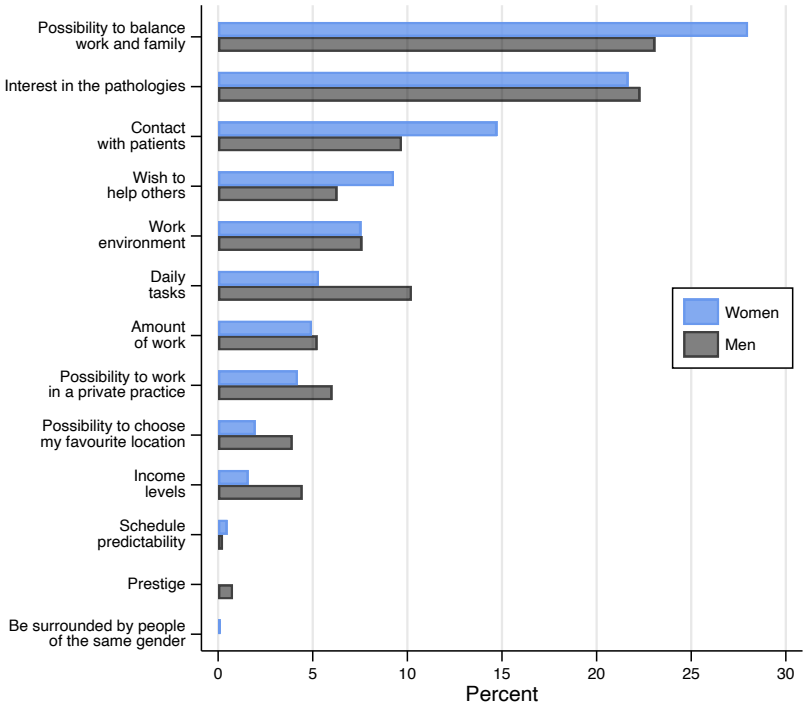
Notes: This figure plots the coefficients $\hat{\beta}$ and 95% confidence intervals in equation (2.1) estimated separately in each decile of the exam score distribution, for 26 medical specialties. Negative (positive) values indicate that on average females are less (more) likely to self-select into 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 2.15: 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 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 refer to 95% confidence intervals computed using heteroskedastic robust standard errors.

Figure 2.16: Most important factor for specialty choice



Notes: This figure shows the share of respondents who selected each of the presented features as the most important factor for choosing their preferred specialty.

Appendix 2.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.

2.B.1 Alternative Definition of Groups with Similar Choice Sets

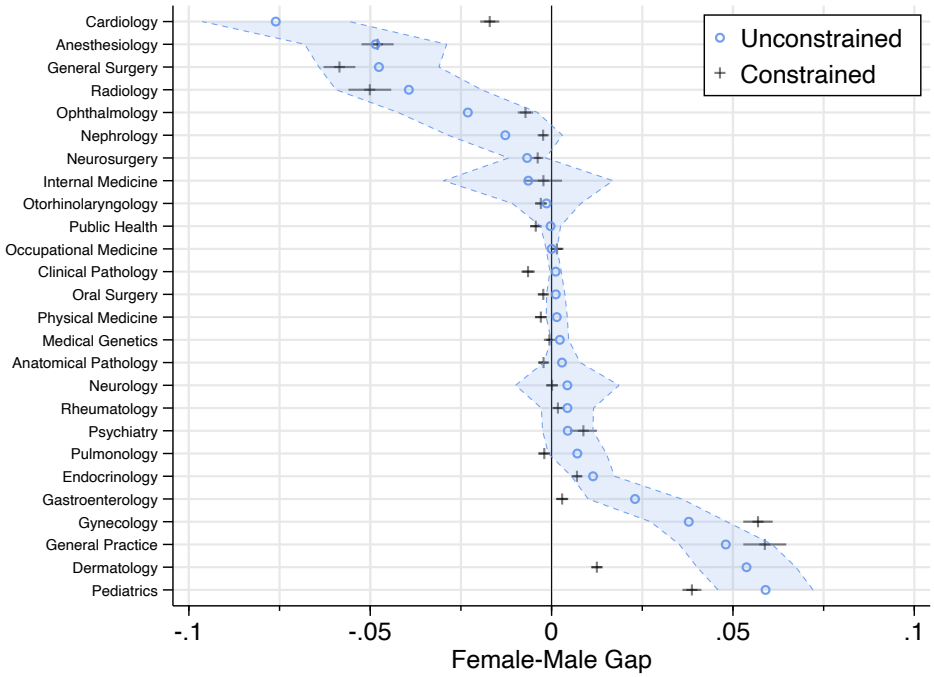
So far, we have considered the choice sets of five individuals with consecutive ranks as similar. Within such groups, the choice set of the best ranked and the worst ranked can at most differ by 4 positions. We now use two alternative, more restrictive definitions of these groups: (i) groups of individual 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 (2.1). The results are shown in Figure 2.17, and comparing them to those displayed in Figure 2.4 shows that our definition of choice set fixed effects is not driving our results.

2.B.2 Alternative Definitions of Unconstrainedness

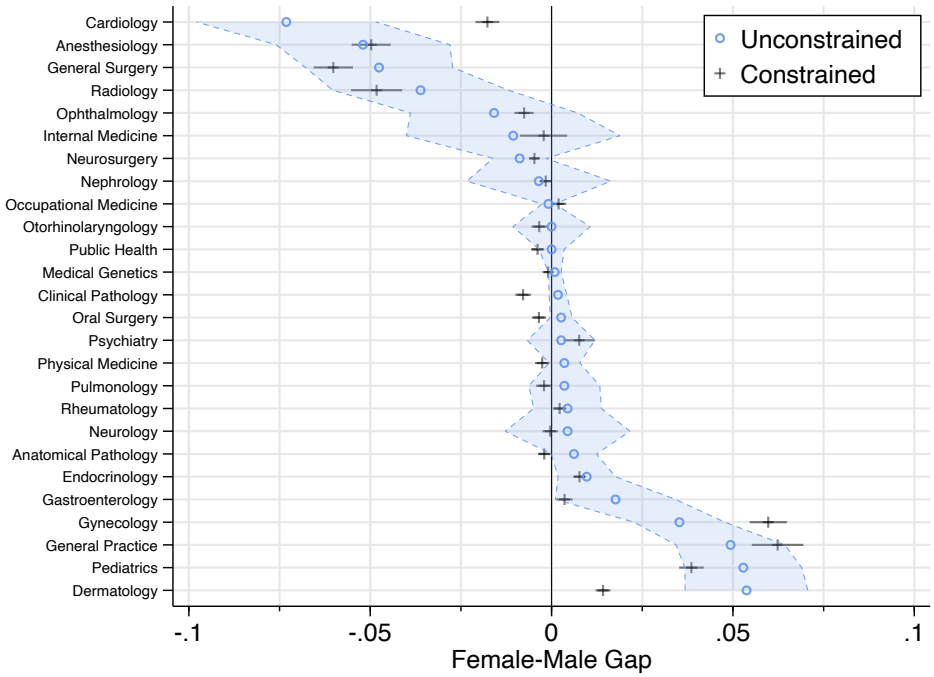
Unconstrainedness is the fact of making the occupational decision while facing no formal barriers to entry into one's preferred position. As a result, unconstrained job seekers are those who pick their job while 100 percent of positions are still available. Given that this definition is restrictive in 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 2.4 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 2.18. 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 2.17: Gender differences in self-selection into specialties, using an alternative definition of choice set fixed effects.

(a) Groups with strictly identical choice sets.



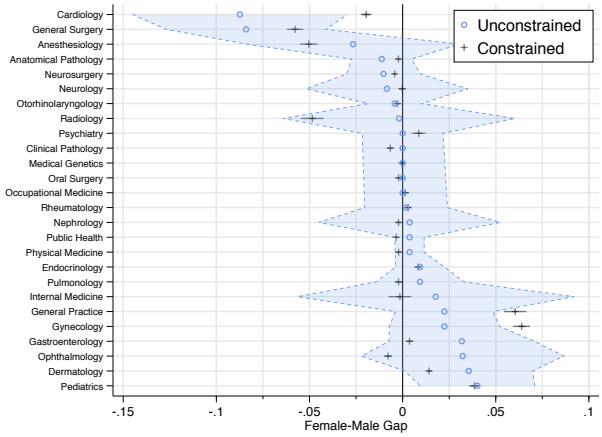
(b) Pairs of one man and one woman of consecutive exam scores.



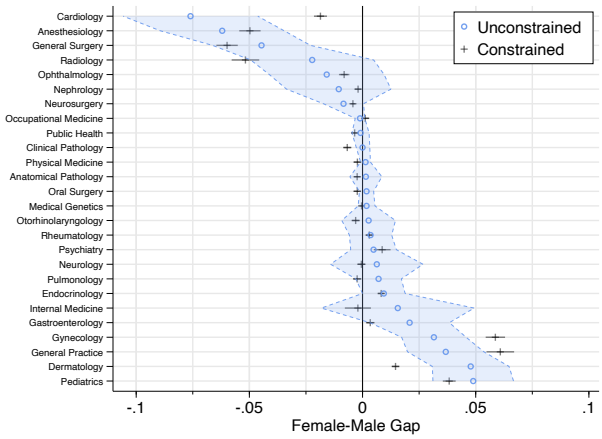
Notes: This figure plots the OLS estimates for the coefficients $\hat{\beta}$ and 95% confidence intervals estimated from equation (2.1) separately by specialty, using (a) groups with strictly identical choice sets, and (b) pairs of one man and one woman of consecutive exam scores as alternative definitions 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 2.18: Gender differences in self-selection into specialties, using alternative definitions of unconstrainedness.

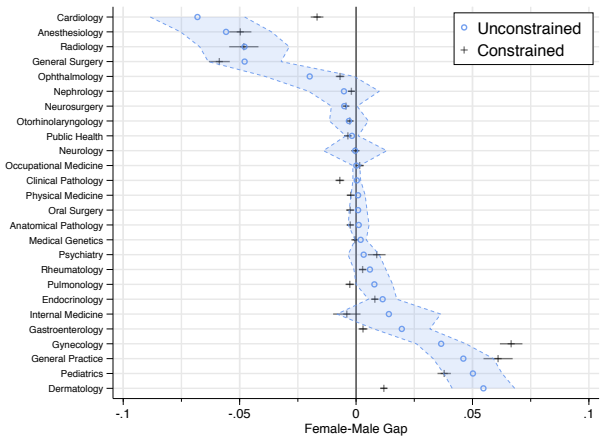
(a) 100% of positions are available.



(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 (2.1) 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.

2.B.3 The Simulation Phase

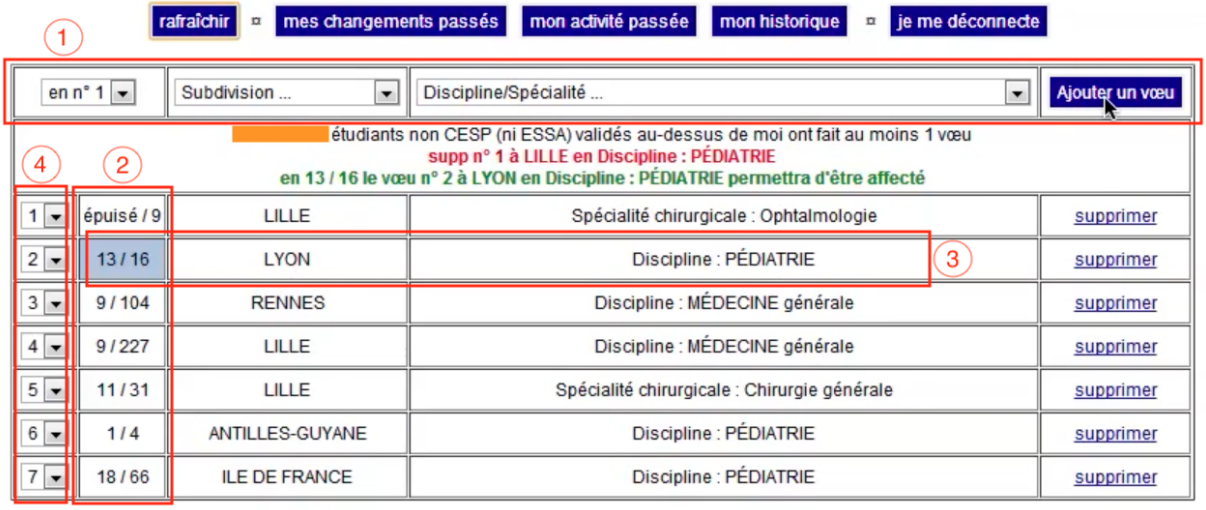
After taking the National Ranking Examinations, and being assigned a rank based of their performance at the exam, students are prompted to take part in a simulation period organised by the CNG on a platform called CELINE. Candidates receive personal credentials which allow them to log into their CELINE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

Figure 2.19 provides an overview of what candidates see during this simulation phase.[29] 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.

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

Figure 2.19: Simulation phase example.



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/`).

Chapter 3

Effects of Welfare Benefits on Subsequent Fertility and Labor Market Decisions[1]

3.1 Introduction

This paper studies the causal effects of welfare benefits supporting parents with low birth weight newborns on their subsequent fertility and the mother's labor market decision. To do so I analyze the effect of granting low socioeconomic status households the necessary resources to allow one of the parents to entirely dedicate their time to the care of their newborn. In particular I use discontinuities on the eligibility criteria of the welfare policy. According to the policy, newborns weighting less than 1500 and 1100 grams, known as *very* and *extremely* low birth weight respectively, are considered to require extra care compared to others with a birth weight above those thresholds.

The legislation, which was implemented in Spain by the end of 2007, supports parents that decide to take care of their at-risk infant. It provides parents with three means-tested benefits. The first benefit consists of providing monthly income transfers to the parent taking care of the at-risk infant, so they can be fully dedicated to childcare. The second benefit, entitles the caregiver to retirement, disability and survivors pension benefits by fully funding their contributions into the national social security fund.[2] Finally the third welfare benefit aims at increasing the skills and information of the caregiver by granting them priority access to vocational training and information courses on home care. Because of the nature of this benefits, I restrict my attention to lower socioeconomic status

[1]I am indebted to my advisors Michèle Belot and Andrea Ichino for their continued encouragement and guidance. I wish to thank Libertad González, Christina Felfe, together with participants at the EUI Microeconometrics Working group for helpful comments.

[2]Spain has a universal health care system in which all citizens are entitled to receive free medical treatment independently of their current and past social security contributions.

households with a very or extremely low birth weight newborn and study their subsequent fertility and labor market decisions.

According to my estimated intention to treat effects, this welfare benefits impacted both the extensive and intensive margin of the fertility decision of only low socioeconomic households. Mothers in low socioeconomic status households with a newborn with a birth weight right below 1100 grams are on average 6 percentage points or 19 percent more likely to have a subsequent child compared to similar mothers with a newborn right above that threshold. This effect is mostly coming from young mothers for whom the benefits are also found to substantially reduce the time to have the subsequent child. The same pattern however, is not present at the 1500 grams birth weight cutoff, where the estimates of the local ITT effect remain very small in size and not statistically different from 0. This might also not be a surprising result if we consider the fact that the monthly income benefit is 36 percent larger at the lower birth weight threshold, making it less likely that households around the upper threshold applied for the welfare benefits.

These effects are presumably coming through the increase in available resources that low socioeconomic status households can devote towards the care of their newborns with extremely low birth weight. Devoting higher resources to a newborn with special needs can potentially improve her health outcomes, granting the caretaker with extra available time. I investigate whether this additional available time translated into higher job holding rates among eligible mothers. Indeed, this is what the results of my analysis show. Mothers in low socioeconomic status with a newborn with a birth weight right below 1100 grams are found to be 16 percentage points or 27 percent more likely to hold a job at the time of their subsequent birth than those with a newborn with a birth weight right above that threshold. Once again no relevant effect is found when looking at similar mothers whose reference newborn was just below and above the 1500 grams threshold.

This paper contributes to the literature that evaluates the effect of means-tested child welfare benefits, or simply child benefits, on subsequent fertility. Although two main difference arise from the common child benefit policies and the one evaluated in this paper. First, it is usually the case that child benefit policies come in the form of cash transfers and tax allowances or a combination of the these two. Second, normally such benefits are directed to large families, i.e. those with at least two or more off-springs that are underage. The main element that the policy evaluated in this paper shares with the most common cash benefits programs is the monetary transfer. The funding of the social security contributions and granting priority access to vocational training and information courses on home care, are unique features of this policy.

Welfare policies targeting parents with newborn children can be divided into child and work-related benefits, e.g. parental leaves. Current research could not unanimously agree on a clear sign nor magnitude of the effects of child benefits on subsequent fertility.

A review of earlier research on international policies in Gauthier (2007) points towards mixed and small effects of child benefits on fertility outcomes. Later research that found positive effects of establishing or increasing benefits linked to giving birth can be found in González (2013), Cohen, Dehejia and Romanov (2013), Riphahn and Wiynck (2017) and González and Trommlerová (2022). On the other hand, Crump, Shah Goda and Mumford (2011) and Baughman and Dickert-Conlin (2003) found negative or non-effect of tax allowance related to children on fertility.

A closely related literature is the one evaluating the effects of maternity and paternity leaves on fertility outcomes. Evidence of this type of work-related policies are also not conclusive. Also Gauthier (2007) surveys the results found on earlier studies focusing on work-related policies, finding that "*results are mixed, with some [studies] concluding that work-related benefits have a small positive impact on fertility, and others finding no evidence of an impact*". More recent studies find also evidence in both directions as Lalive and Zweimüller (2009) and Raute (2019) found positive effect on fertility of duration extension and financial incentives of maternity leave. Dahl et al. (2016) however, do not find effects of extending maternity leave on fertility. Regarding the paternity leave policies Farré and González (2019) report that overall increased the delay in subsequent fertility and had a negative effect on the probability of having a second child for older couples.

There are usually two common features in most studies focusing on the evaluation of child benefits on fertility. The first is the use of a difference-in-difference strategy in order to identify causal effects on fertility outcomes. And the second, is normally the exploration of heterogeneous effects in different socioeconomic status levels. This paper contributes to this literature by using both Regression Discontinuities (RD) design and Difference-in-Discontinuities (diff-in-disc) to estimate causal effects of three welfare benefits on fertility outcomes for low socioeconomic status households with at-risk newborns. The application of a diff-in-disc methodology is justified due to the existence of a potential second treatment changing across the 1500 grams threshold. In particular, one could be concerned by the fact that medical personal might be instructed to provide additional care and treatments to newborns falling below the 1500 grams birth weight cutoff, thus potentially confounding our results.

The use of the diff-in-disc methodology allows us to difference out the effect of the potential additional medical treatment by taking the difference between the period before and after the policy introduction around the 1500 grams discontinuity. To my knowledge only Guldi et al. (2018) use also a birth weight discontinuity at 1200 grams on the eligibility for Supplemental Security Income for disabled infants in the US. Differently from my research however, they focus on child outcomes and the intensive margin of the mothers' labor market decision, while I focus on subsequent fertility outcomes and the extensive margin of the mother's labor decision.

This paper sheds light on the efficacy of potential spillover and mid to long run effects of social policies on fertility outcomes. In addition, to the best of my knowledge, no other study has evaluated the effects of such social benefits package for parents of very and extremely low birth weight newborn on subsequent fertility outcomes. Finally, I believe that the results reported on this paper can easily be extendable and relevant to other European countries where newborn health levels and parental time structures are similar to those in Spain. This paper is structured as follows, Section 3.2 describes the institutional setting of the welfare program. Section 3.3 introduces the data and the estimation methods used in the analysis. Section 3.4 reports and discuses the results and the validity tests and Section 3.5 concludes.

3.2 Institutional Setting

The legislation that entitled low socioeconomic status parents with at-risk newborns to be able to completely devote their time to their care is known as the *dependency law* which was fully introduced and funded by January 2008.[3] The main objective of the law is to promote personal autonomy and care to individuals that require the assistance of others to perform daily routines, who are defined in the law as *dependent* individuals. Certainly, any newborn requires the assistance of others to survive, however the dependency law recognizes very and extremely low birth weight newborn as *dependent* individuals, and thus entitles them to receive State assistance.[4] The main target population of the dependency law however, are elderly individuals and those with certain disabilities. Before the introduction of the dependency law there was no other welfare program using birth weights as an eligibility mechanism.

As explained above, the law provides one of the parents of the eligible newborn with a means tested welfare package that includes the following benefits: (i) monthly income transfer, (ii) full funding of the social security contributions which entitle the beneficiary to retirement, disability and survivors pension benefits and (iii) grants priority access to vocational training and to information courses on home care to increase the parent skills and knowledge about the matter. This benefits are meant to provide parents that fully devote their time to the care of their at-risk newborn with the necessary means to do so.[5] The main condition for eligible parents in order to receive this benefits is that the parent that will be taking care of the dependent infant cannot be working while receiving the benefits.

One caveat regarding data limitation need to be mentioned at this point. Information

[3] Law 39/2006 of December 14th.

[4] 13th additional provision of the mentioned law.

[5] The exact name that appears in the law for the package granting all these welfare benefits is “linked economic benefits for care in the family environment"

on the households that received the benefits was not available to be merged with birth records. This makes the identification of treated parents of low birth-weight newborns impossible in the used data. In order to circumvent this issue, I define the group of mothers who had the highest probability of being eligible for the welfare program using the information contained in the birth records. I restrict my analysis to two groups of non-working mothers: those for who no father was declared in the birth records, and those for whom the declared father is not working or holds a blue-collar occupation. As a consequence, through out the paper we work under the assumption that the mother is the one receiving the benefits to take care of the infant.

Based on health measures and the birth weight of the newborn, the law recognizes one out of three status or levels of "dependency", so called *dependency levels*.[6] Table 3.1 provides a summary of the quantities of the benefits by dependency level for the year 2009. Hence, the caregiver of a newborn considered to be under *great dependency*, i.e. level 3, will receive almost 520€, with the State covering her social security – which at any point will be the minimum contribution set by law – and will be granted priority access to vocational training. The income transfer is means tested and as such the final quantities depend on the individual's income. Table 3.8 shows the proportion of the transfer received by eligible parents. The exact amount of the transfer is established on the basis of how much their earnings exceed an income threshold set by the administration. Even the households in the highest category in terms of earnings will still receive 75% of the income transfer. Also notice, that by using only low socioeconomic status households in my analysis I am focusing on individuals that are eligible to receive most or the entire amounts of the benefits

Table 3.1: Welfare Benefits (2009)

Dependency title	Dependency level	Income transfers	SS contributions	Vocational training
Great	3	519.13€	160.13€	Yes
Severe	2	336,24€	160.13€	Yes
Moderate	1	0€	0€	No

Notes: Extracted from Royal Decree 30/2009 of 30th of January.

Non-working parents of up to 6 months old infants are eligible to receive the welfare benefits if their child suffers *any* of the following circumstances: (i) serious delay in their evolutionary development, (ii) requires life support measures to maintain certain basic physiological functions *or* (iii) birth weight below 1500 grams, very low-birth weight, or 1100 grams, extremely low-birth weight. Eligible parents can apply to receive the welfare

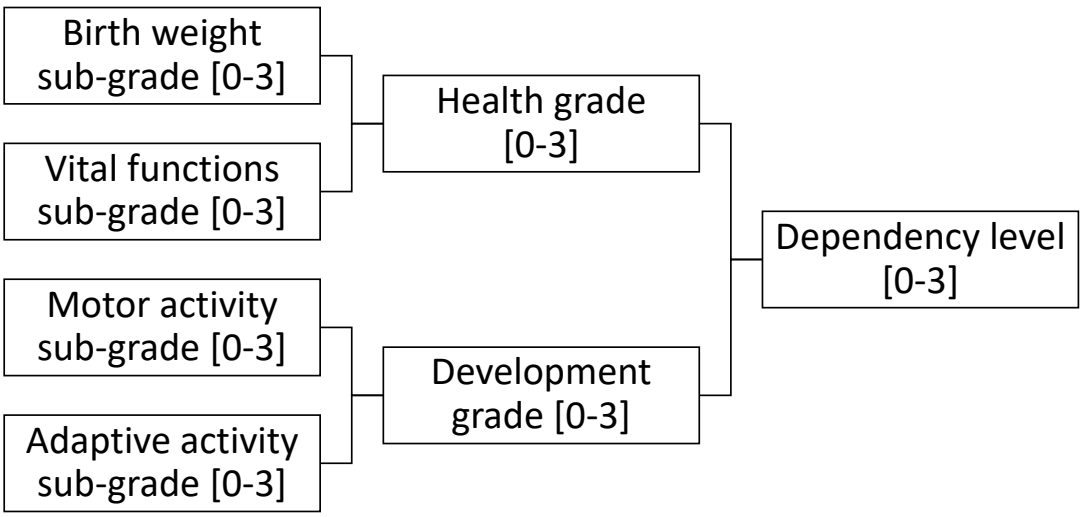
[6]The three recognizable titles in increasing order of the assistance needed are moderate, severe and great dependency, corresponding to levels 1, 2 and 3, respectively.

benefits through their local authority in charge of social services. If the parents fulfill the eligibility criteria, the more stringent one being the incompatibility of receiving the benefits while having a job, then the newborn will be evaluated in order to be assigned a dependency level and the corresponding benefits.[7]

The evaluation of the child health status is performed at the family home by a social assistant which outcome will be a dependency level for the newborn. Figure 3.1 summarizes the scheme followed to determine the dependency level for infants up to 6 months of age. Equations a to c illustrate the rules that establish how the grades and dependency levels are determined. Moreover, table 3.2 shows how the newborn's birth weight is converted into first, a sub-grade, and then into ranges of grades and dependency levels corresponding to each sub-grade. Therefore, a newborn with a birth weight lower than 1100 grams will be automatically considered to have the highest dependency level, i.e. 3. While one weighting between 1100 and 1500 grams can be assigned to dependency levels 2 or 3 depending on other health measures.

The infant will go through biannual re-evaluations of her dependency level, and during those her birth weight will no longer be considered as a factor to determine her dependency level. Finally, at the newborn's third anniversary, dependent children will be evaluated using a different scheme, which is the one used to evaluate the rest of the population.

Figure 3.1: Measures used to determine Newborn's Dependency Levels



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

[7]Formally the parent that will take care of the newborn should not have any other relationship with the Social Security administration, that is they cannot be employed nor receiving any unemployment benefit or pension coming from the Social Security system

$$Health\ grade = max\{Birth\ weight, Vital\ functions\} \tag{a}$$

$$Development\ grade = max\{Motor\ act.\ , Adaptive\ activity\ \} \tag{b}$$

$$Dependency\ level = max\{Health\ grade, Development\ grade\} \tag{c}$$

Table 3.2: Birth Weight into Dependency Levels

Birth weight	Birth weight sub-grade	Health grade	Dependency level
$<$ 1100g	3	3	3
$\geq$ 1100g & $\leq$ 1500g	2	2-3	2-3
$>$ 1500g & $\leq$ 2200g	1	0-3	0-3
$>$ 2200g	0	0-3	0-3

Notes: This table reports how birth weight maps into each dependency level.

3.3 Data and Empirical Strategy

3.3.1 Data

I use the universe of all births registered in Spain throughout the years 2002-2014. This data are contained in the birth-certificates provided by the Spanish National Institute and contain characteristics related to the delivery of every birth register in the country as well as some demographic characteristics of the parents. Due to minor changes in some of the benefits offered by the dependency law, I will restrict the used sample to births recorded from January 2008 until December 2011, both dates included, to identify eligible mothers.

Importantly however, I will still use the information on recorded births from 2012 to 2014 to construct my outcome variables related to subsequent fertility. Moreover, to analyze the effect around the 1500 grams thresholds I will use the pre-policy period, thus extending our sample to births recorded from January 2002 to December 2014.

3.3.2 Empirical Strategy

In this section I discuss three main implications implied by the institutional setting that are relevant for the methodology used in this analysis. The first two implications have its source in the fact that the institutional framework explained above suggests that the

probability of being eligible suffers a *fuzzy* discontinuity at both cutoffs for the following two reasons: (i) the policy is intended for a non-working member of the household and (ii) alternative health related measures other than birth weight also determine eligibility for both dependency levels. I address the first feature of the eligibility criteria by restricting the sample to mothers that report not being working when they had their first child (from now on "reference child") and whose partner, if there is one, is either also without a job or has a low paying occupation.

The second feature of the institutional setting generating fuzzy discontinuities clearly calls for a 2SLS estimation strategy instrumenting the reception of the benefits with the birth weight of the reference child. However, benefits reception is not an observable characteristic in our dataset. Therefore, in the analysis that follows I use the birth weight of the reference child to estimate the causal effects of being eligible to receive the benefits, i.e. the intention-to-treat (ITT) effect.

Certainly, the average effect of receiving the benefits for the recipients would be a much desired policy relevant object. Furthermore, the limitation in data availability is aggravated by the fact that take-up rate of the benefits by parents with low birth weight newborns is known to be certainly low. Therefore, I expect the point estimate of the ITT effects to be considerably smaller, in absolute terms, to the average effect of receiving the benefits on the recipients that would be estimated using a 2SLS strategy. This means that all results provided in my analysis can be evaluated as lower-bound effects of receiving the benefits.

The third implication of the institutional setting, has to do with the fact that, eligibility for extra medical care after birth might be decided using also the 1500 grams threshold, which would imply that two treatments are changing at that birth weight.[8] Thus, the present institutional setting calls for a different methodology to be applied in each cutoff. I apply a difference-in-discontinuities (diff-in-disc) design at 1500 grams while using a regression discontinuity (RD) at the 1100 grams threshold. The former methodology allows us to difference out the effect of the potential additional medical treatment by taking the difference between the before and after policy period around the 1500 grams discontinuity. Applying RD around 1500 grams could then yield biased estimates, as mothers of healthier infants – those affected by a potential increased in medical care – might take different decisions regarding their subsequent fertility from those with a sicker child. On the other hand, using a difference-in-difference approach will result in biased estimates because the probability of having a subsequent delivery is likely to be very different among women that had a child with low birth weight than those who did not. Implying that the parallel trends assumption is likely to be violated.

[8]Official reports from the Spanish Ministry of Health at the time recommended newborns below the 1500 grams birth weight threshold to be transferred into intensive care units.

Previous research has used the discontinuity of medical care at 1500 grams weight cutoffs as a source of exogenous variation in medical treatment – see for instance Almond et al. (2010) and Bharadwaj, Løken and Neilson (2013) – providing evidence of discontinuities at this cutoff on measures of medical care such as hospital stay length, admittance to intensive care unit or survival rate at different ages. Nonetheless, they also discuss and provide evidence supporting the fact that weight-based thresholds "reflected convention rather than biologic criteria" and that practitioners are informed of this fact (Institute of Medicine, 1985). This is why I will also include results of the RD strategy across the 1500 grams threshold and compare them to the diff-in-disc estimates. Differently from the upper threshold of 1500 grams, I am convinced that discontinuities in medical care do not exist at 1100 grams cutoff, as shown by Bharadwaj, Løken and Neilson (2013) for the Chilean and Norwegian context.

The models that I estimate are shown in equation 3.1 for newborns with birth weight right below and above the 1100 grams threshold and equation 3.2 for 1500 grams.

$$Y_i = \alpha + \beta Below1100_i + \gamma_1 f(W) + \gamma_2 f(W) Below1100_i + \delta X_i + \eta_i \tag{3.1}$$

$$\begin{aligned} Y_{it} = {} & \delta_0 + \delta_1 W_{it} + Below1500_i(\gamma_0 + \gamma_1 W_{it}) + Post_t \Big[\alpha_0 \\ & + \alpha_1 W_{it} + Below1500_i(\beta_0 + \beta_1 W_{it})\Big] + \theta X_{it} + \epsilon_{it} \end{aligned} \tag{3.2}$$

Where *Below1100* and *Below1500* are indicator variables taking value 1 if the birth weight of individual i is below the reference threshold and 0 otherwise, $f(W)$ is a polynomial of the birth weight, *Post* takes value 1 if the period t falls after the introduction of the benefits and 0 otherwise. Finally X represent demographic and reference birth characteristics. Demographic controls include whether the mother is married, her age and its squared, level of education (three levels from 2007 only), whether she is of Spanish nationality and the size of the municipality of the reference birth. Reference birth controls include whether the reference birth was of multiple children, the duration of the pregnancy, if there were complications, the time period in between any previous delivery and the reference birth, number of siblings, and year of birth fixed effects. In equation 3.1 I am interested in $\hat{\beta}$, while I take $\hat{\beta}_0$ as the main estimator of interest for equation 3.2. Both methodologies require very similar assumptions to produce unbiased estimates. Regarding diff-in-disc design we follow the assumptions put forward in Grembi, Nannicini and Troiano (2016). In Section 3.4 I indirectly test the continuity of all potential outcomes assumption which common under both methodologies. Bandwidth for the regression discontinuity and difference in discontinuities are computed using the MSE-optimal bandwidth selector. Standard errors in the regression discontinuity are computed using the cluster-robust nearest neighbor variance estimation with a minimum of three neighbors. In both types of regressions standard errors are clustered in birth weights which are

multiples of 5.

3.4 Empirical Results

In this section I first present the results of estimating the intention to treat effects of receiving the welfare benefits on the probability of having a subsequent birth and the time that passed between both births. I also analyze whether the benefits had any impact on the likelihood of holding a job. I show results for women with any parity as well as for those whose first born was the one making them eligible for the benefits, what I will call *any-parity mothers* and *first-time mothers*, respectively. I also estimate heterogeneous effects by whether the mother is below or above 30 years of age.

3.4.1 Effects of the Benefits on Subsequent Fertility

In the first part of the analysis I report the intention to treat estimates of receiving the welfare benefits at both birth weight cutoffs on the probability of giving birth to another child. Following the described institutional setting in Section 3.2, I divided the sample into low socioeconomic status (SES) and non-low socioeconomic status households. Where the former are households in which the mother has no job and the father, if present, has either no job too or works in a low paying occupation. I define non-low socioeconomic status households as those in which both parents have a job. I expect this classification to allow us to distinguishing households who finally received the benefits from those who didn't. I am fairly confident that low socioeconomic status households under our definition were mainly the ones taking up the benefits since they already fulfilled the main eligibility requirement, which is that the caregiver must not hold a job.

Table 3.3 reports the results of estimating equations 3.1 and 3.2 by ordinary least squares. It contains the effect of being eligible to receive the benefits on the likelihood of giving birth to a subsequent child for our two types of socioeconomic status households for all parity and first-time mothers and in both birth weight thresholds, respectively. Columns 1 and 4 report the estimated coefficients without any controls, 2 and 5 adds demographic controls, 3 and 6 combines both demographics and reference birth controls. In line with my expectations, when focusing on non-low socioeconomic status (SES) households the estimates remain always small and not statistically significant at both birth weights thresholds. The same estimation process is applied to the sample of low SES households, colums 4 to 6, and in this case differences between the reference newborn being right below or above the 1100 grams arise.

The estimated ITT effects at the lower cutoff are positive and statistically significant in the three specifications. Mothers of any parity who's reference newborn had a birth

Table 3.3: Effects of the Benefits on a Subsequent Birth by Socioeconomic Status

	Non-low SES			Low SES		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: 1100g (RD)			
All parity mothers	0.0026	-0.0215***	0.0068	0.0371***	0.0542***	0.0623***
	(0.0039)	(0.0041)	(0.0041)	(0.0097)	(0.0106)	(0.0104)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.23	0.23	0.23	0.19	0.19	0.19
Bandwidth	76	112	97	256	213	178
Observations	1,856	3,013	2,227	1,890	1,649	1,332
First-time mothers	0.0057	-0.0168*	-0.0080	0.0648**	0.0824***	0.0948***
	(0.0088)	(0.0066)	(0.0059)	(0.0202)	(0.0217)	(0.0192)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.30	0.30	0.30	0.27	0.27	0.27
Bandwidth	68	77	81	190	158	160
Observations	1,114	1,237	1,357	725	639	656
			Panel B: 1500g (Dif-in-Disc)			
All parity mothers	-0.0003	0.0000	-0.0000	0.0001	-0.0001	-0.0000
	(0.0004)	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.33	0.33	0.33	0.25	0.25	0.25
Bandwidth	157	170	175	299	342	229
Observations	10,695	11,228	11,654	6,276	7,829	5,074
First-time mothers	0.0006	-0.0000	0.0001	0.0007	0.0009	0.0008
	(0.0007)	(0.0006)	(0.0005)	(0.0005)	(0.0007)	(0.0008)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.45	0.45	0.45	0.40	0.40	0.40
Bandwidth	134	155	177	221	196	175
Observations	6,389	7,428	8,178	2,422	1,971	1,819

Notes: Panel A and B report the estimated coefficients β and $beta_0$ in equations 3.1 and 3.2 around the 1100 and 1500 grams threshold, respectively. Low SES contains households in which the mother has no job and the father, if present, has either no job or works in a low paying occupation. Non-low SES households are those in which both parents have a job. Demographic controls include whether the mother is married, her age and its squared, level of education (three levels from 2007 only), whether she is of Spanish nationality and the size of the municipality of the reference birth. Reference birth controls include whether the reference birth was of multiple children, the duration of the pregnancy, if there were complications, the time period in between any previous delivery and the reference birth, number of siblings, and year of birth fixed effects. Bandwidth for both the regression discontinuity and difference in discontinuities are computed using the MSE-optimal bandwidth selector. Standard errors in the regression discontinuity are computed using the cluster-robust nearest neighbor variance estimation with a minimum of three neighbors. In both types of regressions standard errors are clustered in birth weights which are multiples of 5. *** p<0.01, ** p<0.05, * p<0.1.

weight right below 1100 grams are 6.2 percentage points more likely to have a subsequent child than mothers with a newborn right above that birth weight threshold. Moreover, for first-time mothers the effect increases to 9.5 percentage points. Considering that the average probability of having a subsequent birth is 19 and 25 percent for these two groups

of mothers, these translates into the policy having an average increase in the probability of a subsequent birth of 33 and 38 percent, respectively. The same pattern however, is not present at the 1500 grams cutoff, where the estimates of the local ITT effect remain very small in size and not statistically different from 0. This might also not be a surprising result if I consider the fact that intuitively, *ceteris paribus*, a mother will be more likely to apply for the benefits the larger these are. As shown in Table 3.1 the monthly income benefit is 36 percent larger at the lower birth weight threshold.

I am interested in understanding whether there are some particular groups of women that might be more likely affected by the benefits. For this reason, I perform the same analysis focusing only on households with a lower-SES differentiating women who are below from those above 30 years of age. Table 3.4 reports the result by age group for mothers of any parity and first-time mothers. It shows how mothers below 30 years of age with 1100 grams newborns are 10 percentage points or 37 percent more likely to have a subsequent birth. However, the effect of the benefits is not present for first-time mothers of either age group. The estimated effects for the older group of women in the lower threshold are very small and not statistically different from 0. This means that the main estimated local ITT effect for the mothers with 1100 grams newborns reported in Table 3.3 is coming from those who are under 30 years old. Once more, there are no apparent effects of receiving the benefits at 1500 grams as the estimates are very small and not statistically different from 0.

The analysis shows how the benefits, which their main objective is to provide support to households with newborns requiring special care, had an impact on the likelihood of having a subsequent child. The intensive margin of having a subsequent birth, that is the time to the next delivery, is another policy relevant measure that I am interested in analysing. To that end I restrict the sample to low socioeconomic status households who had a subsequent child during the period covered in the data. Table 3.5 reports the results of estimating equation 3.1 and 3.2 using the months to the next delivery as the dependent variable within the two age groups. The estimated ITT effect of the benefits shows how young mothers with newborns reduced the time it took them to have a subsequent birth by more than 10 months. This effect is not detected for mothers older than 30, first-time mothers of both age groups nor when looking right above and below the 1500 grams birth weight threshold. One caveat of these analysis that needs to be considered when interpreting these results, is the low number of observations that are used in the regression discontinuity analysis around the 1100 grams threshold.

Table 3.4: Effects of the Benefits on a Subsequent Birth by Age Group

	Below 30			Above 30		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1100g (RD)						
All parity mothers	0.0503**	0.0517***	0.1007***	-0.0192	-0.0035	0.0022
	(0.0166)	(0.0148)	(0.0163)	(0.0315)	(0.0265)	(0.0245)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.27	0.27	0.27	0.11	0.11	0.11
Bandwidth	147	117	149	158	179	158
Observations	572	502	573	626	682	627
First-time mothers	0.0220	0.0096	0.0406	0.0112	0.0573	0.0481
	(0.0321)	(0.0229)	(0.0273)	(0.0608)	(0.0573)	(0.0490)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.32	0.32	0.32	0.20	0.20	0.20
Bandwidth	130	96	127	158	144	153
Observations	325	222	325	260	246	258
Panel B: 1500g (Dif-in-Disc)						
All parity mothers	-0.0003	-0.0002	-0.0001	0.0001	0.0003	-0.0001
	(0.0005)	(0.0005)	(0.0006)	(0.0002)	(0.0004)	(0.0002)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.40	0.40	0.40	0.13	0.13	0.13
Bandwidth	235	256	217	221	200	234
Observations	2,298	2,506	2,178	2,807	2,286	2,888
First-time mothers	0.0010	0.0006	0.0005	0.0005	0.0004	0.0003
	(0.0010)	(0.0007)	(0.0008)	(0.0004)	(0.0004)	(0.0004)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.53	0.53	0.53	0.27	0.27	0.27
Bandwidth	195	219	204	302	301	274
Observations	1,049	1,271	1,238	1,589	1,589	1,321

Notes: Panel A and B report the estimated coefficients β and $beta_0$ in equations 3.1 and 3.2 around the 1100 and 1500 grams threshold, respectively. Estimations are performed using mothers who are younger and older of 30 years of age. The sample is further restricted to households in which the mother has no job and the father, if present, has either no job or works in a low paying occupation. Demographic controls include whether the mother is married, her age and its squared, level of education (three levels from 2007 only), whether she is of Spanish nationality and the size of the municipality of the reference birth. Reference birth controls include whether the reference birth was of multiple children, the duration of the pregnancy, if there were complications, the time period in between any previous delivery and the reference birth, number of siblings, and year of birth fixed effects. Bandwidth for both the regression discontinuity and difference in discontinuities are computed using the MSE-optimal bandwidth selector. Standard errors in the regression discontinuity are computed using the cluster-robust nearest neighbor variance estimation with a minimum of three neighbors. In both types of regressions standard errors are clustered in birth weights which are multiples of 5. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5: Effects of the Benefits on Months to a Subsequent Birth by Age Group

	Below 30			Above 30		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: 1100g (RD)			
All parity mothers	-3.4763	-4.0678*	-10.1125***	-6.8712	-3.3303	-5.0678
	(1.7835)	(1.8160)	(1.5044)	(6.3654)	(7.7418)	(8.8772)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	37.56	37.54	37.55	36.02	36.02	36.02
Bandwidth	184	153	125	179	163	178
Observations	155	138	112	74	73	74
First-time mothers	-5.8370	-4.3164	-4.8984	2.2846	8.1955	7.8723
	(4.9137)	(4.8880)	(4.7081)	(5.4748)	(5.1278)	(4.7213)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	37.90	37.90	37.90	36.85	36.87	36.87
Bandwidth	204	196	206	227	234	234
Observations	144	120	144	54	56	56
			Panel B: 1500g (Dif-in-Disc)			
All parity mothers	0.0602	0.1075	0.0541	0.0138	-0.0223	-0.0174
	(0.0509)	(0.0696)	(0.0455)	(0.0668)	(0.0580)	(0.0443)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	53.08	53.08	53.08	44.60	44.60	44.60
Bandwidth	212	182	208	250	295	316
Observations	627	485	616	330	380	439
First-time mothers	0.0491	0.0391	0.0513*	-0.0057	0.0083	-0.0210
	(0.0252)	(0.0242)	(0.0240)	(0.0499)	(0.0555)	(0.0417)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	52.97	52.97	52.97	45.49	45.49	45.49
Bandwidth	354	388	353	307	279	341
Observations	720	777	720	278	240	299

Notes: Panel A and B report the estimated coefficients β and $beta_0$ in equations 3.1 and 3.2 around the 1100 and 1500 grams threshold, respectively. Estimations are performed using mothers who are younger and older of 30 years of age. The sample is further restricted to households in which the mother has no job and the father, if present, has either no job or works in a low paying occupation. Demographic controls include whether the mother is married, her age and its squared, level of education (three levels from 2007 only), whether she is of Spanish nationality and the size of the municipality of the reference birth. Reference birth controls include whether the reference birth was of multiple children, the duration of the pregnancy, if there were complications, the time period in between any previous delivery and the reference birth, number of siblings, and year of birth fixed effects. Bandwidth for both the regression discontinuity and difference in discontinuities are computed using the MSE-optimal bandwidth selector. Standard errors in the regression discontinuity are computed using the cluster-robust nearest neighbor variance estimation with a minimum of three neighbors. In both types of regressions standard errors are clustered in birth weights which are multiples of 5. *** p<0.01, ** p<0.05, * p<0.1.

3.4.2 Effects of the Benefits on Employment

According to the estimated ITT effects, the welfare benefits impacted both the extensive and intensive margin of the fertility decision of eligible households. This effect is prob-

ably coming through the increase in available resources that low socioeconomic status households could dedicate to the care of their very low birth newborn. Dedicating higher resources to the new born with special needs can potentially improve her health outcomes allowing the caretaker to enter the labor force. We now analyze whether being eligible to receive the benefits had any effect on the likelihood of having a job for mothers who had a subsequent child. For single non-working mothers, households in which both members do not have a job or the father has a low paying job, the potential increase in the health outcomes of their very low birth weight newborn resulting from receiving the benefits could induce the mother to enter the labor force.

To analyze whether this was the case I use the employment information present in the register of the subsequent birth. I classify mothers who report being a housewife or a student as not having a job and remove all mothers who receive a retirement pension from the sample to facilitate the interpretation of the results. The ITT estimates of receiving the benefits on the likelihood of holding a job for mothers with a subsequent birth are reported in Table 3.6 by socioeconomic status group. Mothers in low SES households with a newborn with a birth weight right below 1100 grams are found to be 15.8 percentage points or 26.8 percent more likely to hold a job at the time of their subsequent birth than those with a newborn with a birth weight right above that threshold. No effect is detected for mothers in non-low SES when comparing them across the same birth weight threshold. For mothers for whom the reference birth was their first birth, the effect of the benefits on their likelihood of holding a job increases to 17.3 percentage points or 30.4 percent. Once again no relevant effect is found when looking at similar mothers whose reference newborn was just below and above the 1500 grams threshold.

Table 3.7 reports the same estimated effect for low SES households depending on the age group of the mother when she gave birth to the reference newborn. Mothers who are above 30 years of age when the reference child is born are found to be driving the main effect of the welfare benefits. This is true for all parity mothers as well as first-time mothers. Around the 1100 grams threshold, mothers older than 30 are 21.2 percentage points or 32.6 percent more likely to hold a job during their subsequent delivery, compared to 11.4 percentage points or 21.1 percent for younger mothers. The estimated ITT effects of the benefits for both age groups of first-time mothers with a reference newborn with a birth weight around that threshold are even higher in magnitude, 26.4 percentage points (41.9 percent) and 11 percentage points (20.4 percent), respectively. Finally, no relevant effect of the benefits is detected across the birth weight threshold of 1500 grams.

Table 3.6: Effects of the Benefits on Job Holding by Socioeconomic Status

	Non-low SES			Low SES		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: 1100g (RD)			
All parity mothers	-0.0037	-0.0110	-0.0011	0.1353***	0.1701***	0.1582***
	(0.0085)	(0.0094)	(0.0089)	(0.0319)	(0.0421)	(0.0409)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.79	0.79	0.79	0.59	0.59	0.59
Bandwidth	216	166	192	153	114	112
Observations	4,564	3,499	3,907	1,076	878	877
First-time mothers	-0.0080	-0.0149	0.0029	0.1500***	0.1611***	0.1725***
	(0.0093)	(0.0101)	(0.0085)	(0.0377)	(0.0444)	(0.0418)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.81	0.81	0.81	0.57	0.57	0.57
Bandwidth	217	178	242	99	93	102
Observations	3,116	2,490	3,429	329	322	440
			Panel B: 1500g (Dif-in-Disc)			
All parity mothers	0.0000	0.0001	0.0001	-0.0005	-0.0004	-0.0005
	(0.0004)	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0004)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.80	0.80	0.80	0.60	0.60	0.60
Bandwidth	164	225	226	239	280	223
Observations	9,807	13,785	13,870	4,493	5,126	4,343
First-time mothers	-0.0004	-0.0006*	-0.0004	-0.0017**	-0.0016**	-0.0014**
	(0.0003)	(0.0003)	(0.0002)	(0.0005)	(0.0005)	(0.0005)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.82	0.82	0.82	0.53	0.53	0.53
Bandwidth	173	188	219	238	236	229
Observations	7,183	7,602	9,361	2,181	2,180	2,117

Notes: Panel A and B report the estimated coefficients β and $beta_0$ in equations 3.1 and 3.2 around the 1100 and 1500 grams threshold, respectively. Low SES contains households in which the mother has no job and the father, if present, has either no job or works in a low paying occupation. Non-low SES households are those in which both parents have a job. Demographic controls include whether the mother is married, her age and its squared, level of education (three levels from 2007 only), whether she is of Spanish nationality and the size of the municipality of the reference birth. Reference birth controls include whether the reference birth was of multiple children, the duration of the pregnancy, if there were complications, the time period in between any previous delivery and the reference birth, number of siblings, and year of birth fixed effects. Bandwidth for both the regression discontinuity and difference in discontinuities are computed using the MSE-optimal bandwidth selector. Standard errors in the regression discontinuity are computed using the cluster-robust nearest neighbor variance estimation with a minimum of three neighbors. In both types of regressions standard errors are clustered in birth weights which are multiples of 5. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.7: Effects of the Benefits on Job Holding by Age Group

	Below 30			Above 30		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: 1100g (RD)			
All parity mothers	0.1145***	0.1103***	0.1141***	0.1920**	0.1956**	0.2122***
	(0.0321)	(0.0316)	(0.0326)	(0.0620)	(0.0626)	(0.0623)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.54	0.54	0.54	0.65	0.65	0.65
Bandwidth	185	194	182	89	84	89
Observations	595	613	593	282	282	283
First-time mothers	0.1516***	0.1451***	0.1102**	0.1698*	0.2185**	0.2638***
	(0.0416)	(0.0385)	(0.0367)	(0.0801)	(0.0734)	(0.0713)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.53	0.53	0.53	0.63	0.63	0.63
Bandwidth	91	94	95	114	124	133
Observations	198	199	199	184	194	199
			Panel B: 1500g (Dif-in-Disc)			
All parity mothers	-0.0002	0.0003	0.0006	-0.0002	-0.0012	-0.0008
	(0.0005)	(0.0006)	(0.0007)	(0.0012)	(0.0011)	(0.0012)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.52	0.52	0.52	0.66	0.66	0.66
Bandwidth	268	231	207	112	132	115
Observations	2,210	1,988	1,844	1,298	1,447	1,299
First-time mothers	0.0025	0.0020	0.0014	-0.0033**	-0.0036**	-0.0036*
	(0.0016)	(0.0023)	(0.0019)	(0.0012)	(0.0013)	(0.0014)
Demographic controls	No	Yes	Yes	No	Yes	Yes
Reference birth controls	No	No	Yes	No	No	Yes
Mean	0.47	0.47	0.47	0.59	0.59	0.59
Bandwidth	165	132	129	157	159	159
Observations	814	648	620	679	679	679

Notes: Panel A and B report the estimated coefficients β and $beta_0$ in equations 3.1 and 3.2 around the 1100 and 1500 grams threshold, respectively. Estimations are performed using mothers who are younger and older of 30 years of age. The sample is further restricted to households in which the mother has no job and the father, if present, has either no job or works in a low paying occupation. Demographic controls include whether the mother is married, her age and its squared, level of education (three levels from 2007 only), whether she is of Spanish nationality and the size of the municipality of the reference birth. Reference birth controls include whether the reference birth was of multiple children, the duration of the pregnancy, if there were complications, the time period in between any previous delivery and the reference birth, number of siblings, and year of birth fixed effects. Bandwidth for both the regression discontinuity and difference in discontinuities are computed using the MSE-optimal bandwidth selector. Standard errors in the regression discontinuity are computed using the cluster-robust nearest neighbor variance estimation with a minimum of three neighbors. In both types of regressions standard errors are clustered in birth weights which are multiples of 5. *** p<0.01, ** p<0.05, * p<0.1.

3.4.3 Validity tests

In this section I evaluate the main assumptions of the two methodologies that have been used to estimate the results presented above. As mentioned in Section 3.3 both methodologies have very similar assumptions. For a detail discussion on the assumptions of the

diff-in-disc methodology see Grembi, Nannicini and Troiano (2016). The first main assumption for both methodologies is the need for all potential outcomes to be continuous across the cutoff. In the case of diff-in-disc this assumption has to hold in the pre- and post-treatment period. This first assumption requires that there is no-sorting above or below the main cutoffs in any period of time, meaning that neither the parents nor the medical personnel where able to manipulate the birth weight. Using the minimum birth weight among all newborns of each delivery as our running variable, and the manipulation test proposed in Cattaneo, Jansson and Ma (2018) the null hypothesis of no manipulation is rejected. As already discussed in Section 3.3 birth weight data is subject to a large degree of heaping on digits multiples of round numbers such as 10 or 50. Figure 3.2 which plots the densities for every 10 bins around each cutoff, can help to make our case clear. First it clearly shows how weight digits that are multiples of 50 take higher densities. Second, such rule of heaping does not seem to be exacerbated at the cutoffs. Third, densities of bins just above and below the cutoff are very similar, which speaks in favour of the hypothesis of no manipulation of the birth weight. However, comparing densities just above and below the cutoffs does not allow us to exclude the possibility that a similar amount of individuals could have sorted just above and below the cutoffs.[9]

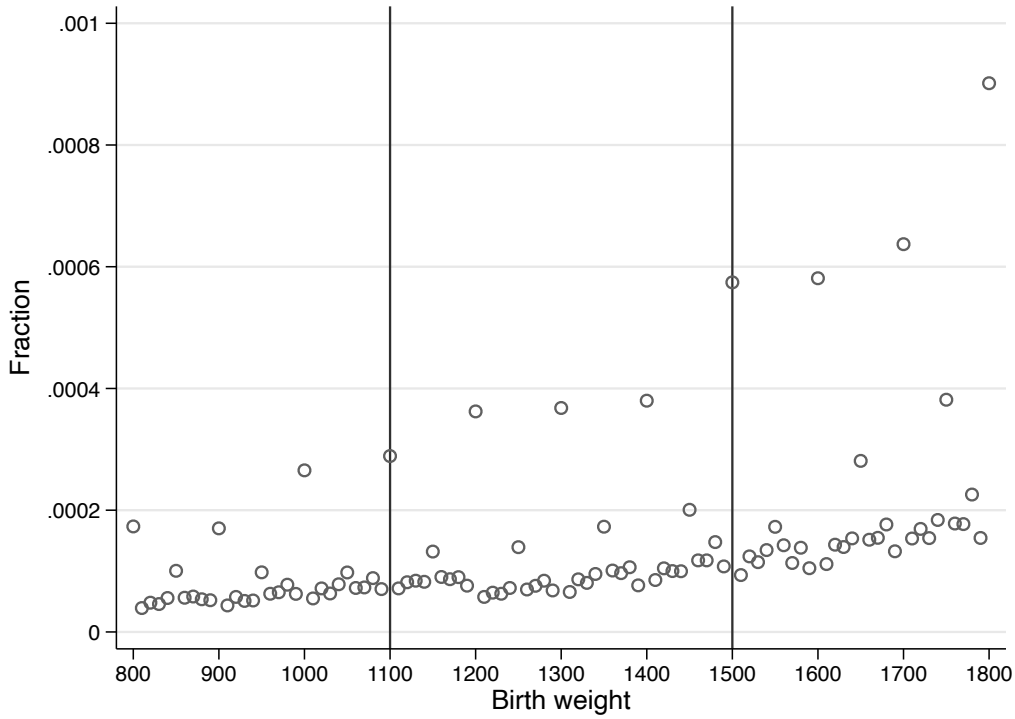
Thus, I can be confident at concluding that the heaping is potentially the main reason why the running variable cannot pass the manipulation test. I will next proceed at testing whether the heaping of the running variable around the threshold can be considered as good as random. To do so, I will follow two approaches, one is inspired by Panel B in Figure 1 of Barreca, Lindo and Waddell (2015), while the other follows the authors main recommendation. In the first approach, I graphically show that the mean values for a set of characteristics regarding parental and birth characteristics do not take significantly different values in unit-bins that are more susceptible to suffer heaping (multiples of 10) than those that are not (the rest of unit-bins). Figures 3.4 and 3.5 show how mean values of the selected characteristics at bins that correspond to multiples of 10 do not vary significantly from those that are not in those type of bins. My second approach, is a more rigorous analysis of the previous approach. Estimating equation 3.3 will allow us to identify whether there are systematic difference between heaped and non-heaped data.

$$X_i = \gamma_0 + \gamma_1 \mathbb{1}\left(W_i = Z_n\right) + u_i \tag{3.3}$$

Where X_i and W_i represent a covariate and birth weight for individual i respectively, Z are all the multiples of a particular number n. More precisely, by estimating regression equation 3.3 in a bandwidth around each cutoff, I can test whether the value of covariate

[9]Figure 3.3 in the Appendix plots the same scatters before and after the policy period, and same conclusions can be extended to each period.

Figure 3.2: Fraction of Births in 10 grams Bins



Notes: This figure plots the fraction of births in bins of 10 grams birth weights around the policy relevant thresholds.

X at a given data heap Z, systematically varies from its non-heaped neighbours around the cutoffs. In order to reject the null hypothesis of random heaping we would need to find that most of $\hat{\gamma}_1$ are statistically significantly different from 0. Tables 3.9 and 3.9 in the Appendix show the results of regression equation 3.3 using as a heap points multiples of 10 i.e. $n = 10$, in a bandwidth of 100 grams around each cutoff. As can be seen very few estimates are statistically different from 0, and those that are, tend to be very small. For instance Panel B of Table 3.10 shows how deliveries falling in weight bins that are multiple of 10 are estimated to have only 0.27 gestational weeks more than newborns with other birth weights.

3.5 Conclusion

This paper analyzes the effects of a set of welfare benefits targeted to households with a low birth weight newborn on their subsequent fertility and the mother's labor market decision. It uses discontinuities on the eligibility criteria of the welfare policy to estimate the intention to treat effect of receiving the benefits. According to the policy, newborns weighting less than 1500 and 1100 grams are considered to require extra care and therefore the caregiver parent is entitled to receive additional support. The benefits were designed

to provide the necessary resources to the caregiver to dedicate themselves to the care of their newborn. They consist of a monthly income transfer, fully funded social security contributions and granting them priority access to vocational training and information courses on home care. Because of the means tested design of the benefits, lower socioeconomic status households with a very or extremely low birth weight newborn are the most likely recipients and the focus of this study.

Estimated intention to treat effects indicate that the welfare benefits impacted both the extensive and intensive margin of the fertility decision. This is only found for low socioeconomic households with no effect detected for the rest of household. Mothers in low socioeconomic status households having a newborn with a birth weight right below 1100 grams are on average 6 percentage points or 19 percent more likely to have a subsequent child compared to similar mothers with a newborn right above that threshold. The effect is mostly coming from young mothers for whom the benefits are also found to reduce the time to have the subsequent child. The fact that the no effect is detected at the upper birth weight cutoff could be explained by the potential lower take-up rate at that part of the birth weight distribution. Which could be due to the fact that they would receive a lower monthly income benefit. Moreover, I find that mothers in low socioeconomic status households having a newborn with a birth weight right below 1100 grams are 16 percentage points or 27 percent more likely to hold a job at the time of their subsequent birth than those having a newborn with a birth weight right above that threshold.

The mechanisms that we can put forward to rationalize these findings have to do with the increase in available resources that low socioeconomic status households can devote towards the care of their newborns with extremely low birth weight. Devoting higher resources to a newborn with special needs can potentially lead to improved health outcomes, granting the caretaker with the opportunity to enter the labor market.

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3.6 Appendix

Table 3.8: Percentage of income transfer and earnings

=======	Percentage of Income Transfer
Earnings < PIMEI	100
PIMEI < earnings < 2×PIMEI	95
2×PIMEI < earnings < 3×PIMEI	90
3×PIMEI < earnings < 4×PIMEI	85
4×PIMEI < earnings < 5×PIMEI	80
Earnings > 5×PIMEI	75

Notes: This table shows the relationship between the amount of the income transfer received by the beneficiary with their individual earnings. PIMEI stands for Public Indicator of Multiple Effects Income.

Table 3.9: Differences in parental characteristics between 10 grams multiple and single grams bins

	(1) Married	(2) Years married	(3) Age (M)	(4) Spanish (M)	(5) Occupation (M)	(6) Age (F)	(7) Spanish (F)	(8) Occupation (F)
Panel A: Around 1100g post-benefits								
Multiple of 10	0.041*	0.119	-0.030	-0.007	-0.034	0.462	0.006	0.014
	(0.019)	(0.154)	(0.266)	(0.019)	(0.087)	(0.403)	(0.023)	(0.070)
Bandwidth	100	100	100	100	100	100	100	100
Observations	5,739	4,223	5,739	5,713	5,739	5,739	5,497	5,739
Panel B: Around 1500g pre-benefits								
Multiple of 10	0.011	-0.041	-0.148	-0.006	0.100	-0.179	-0.008	0.121
	(0.024)	(0.121)	(0.216)	(0.014)	(0.080)	(0.334)	(0.021)	(0.063)
Bandwidth	100	100	100	100	100	100	100	100
Observations	7,847	5,561	7,847	7,843	7,847	7,847	7,612	7,847
Panel C: Around 1500g post-benefits								
Multiple of 10	0.005	0.344*	0.279	-0.024	0.043	0.133	-0.037	0.045
	(0.022)	(0.141)	(0.217)	(0.016)	(0.098)	(0.346)	(0.022)	(0.060)
Bandwidth	100	100	100	100	100	100	100	100
Observations	8,704	6,477	8,704	8,666	8,704	8,704	8,392	8,704

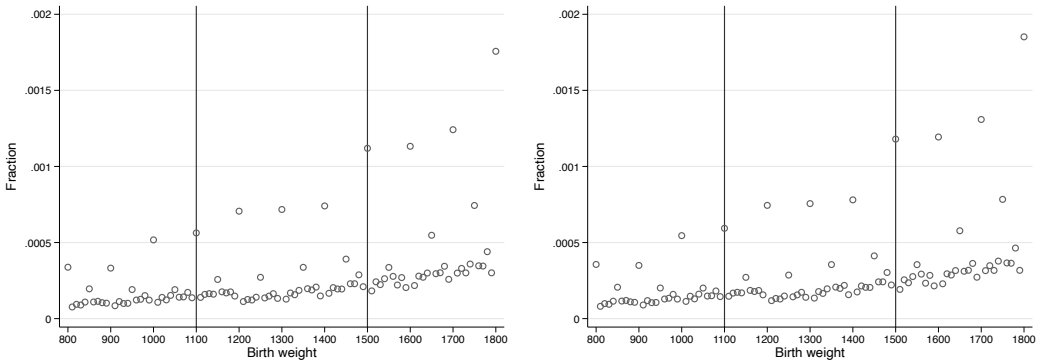
Notes: This table reports the estimated coefficient γ_1 of equation 3.3. It uses all births after or before the policy implementation with a birth weight in a bandwidth of 100 grams around each threshold. Standard errors clustered at bins of multiple of 10 grams *** p<0.01, ** p<0.05, * p<0.1.

Table 3.10: Differences in birth characteristics between 10 grams multiple and single grams bins

	(1) Municipality size	(2) Multiple delivery	(3) 24h alive	(4) Gestation	(5) Complications	(6) Inter-gestational	(7) Siblings	(8) Year
				Panel A: Around 1100g post-benefits				
Multiple of 10	-0.041	0.026	-0.019*	0.127	-0.023	1.431	0.010	0.045
	(0.083)	(0.023)	(0.009)	(0.278)	(0.020)	(1.677)	(0.031)	(0.044)
Bandwidth	100	100	100	100	100	100	100	100
Observations	5,739	5,739	5,739	4,928	5,739	5,556	5,739	5,739
				Panel B: Around 1500g pre-benefits				
Multiple of 10	-0.020	0.026	-0.009	0.276*	-0.046*	-3.692	0.036	-0.009
	(0.049)	(0.019)	(0.008)	(0.122)	(0.017)	(1.967)	(0.028)	(0.055)
Bandwidth	100	100	100	100	100	100	100	100
Observations	7,847	7,847	7,847	7,197	7,847	6,204	7,847	7,847
				Panel C: Around 1500g post-benefits				
Multiple of 10	-0.033	0.022	-0.008	0.152	-0.012	2.138	0.089***	0.039
	(0.052)	(0.016)	(0.007)	(0.170)	(0.021)	(1.438)	(0.020)	(0.039)
Bandwidth	100	100	100	100	100	100	100	100
Observations	8,704	8,704	8,704	7,516	8,704	8,426	8,704	8,704

Notes: This table reports the estimated coefficient γ_1 of equation 3.3. It uses all births after or before the policy implementation with a birth weight in a bandwidth of 100 grams around each threshold. Standard errors clustered at bins of multiple of 10 grams *** p<0.01, ** p<0.05, * p<0.1.

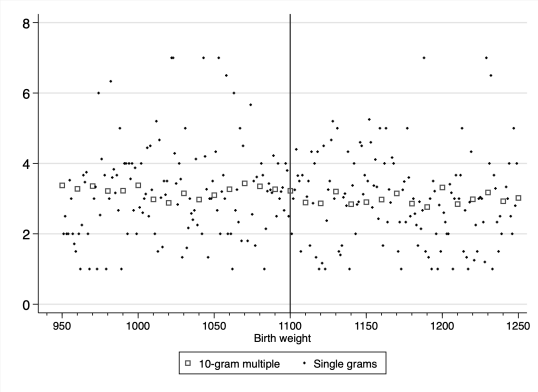
Figure 3.3: Fraction of Births in 10 grams Bins Before and After



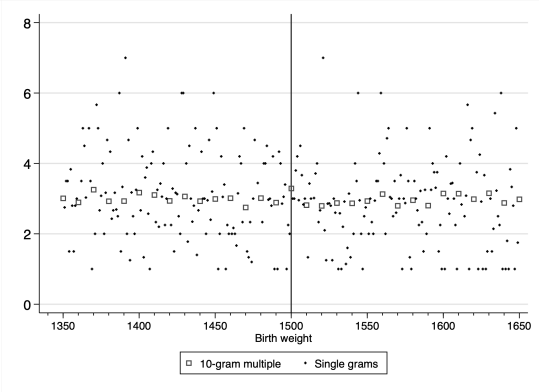
Notes: Notes: This figure plots the fraction of births in bins of 10 grams birth weights around the policy relevant thresholds before and after the introduction of the benefits.

Figure 3.4: Bin Mean Values of Parental Characteristics

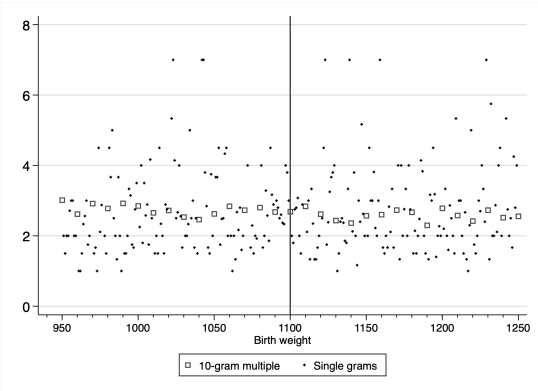
(a) Mother's occupation around 1100g



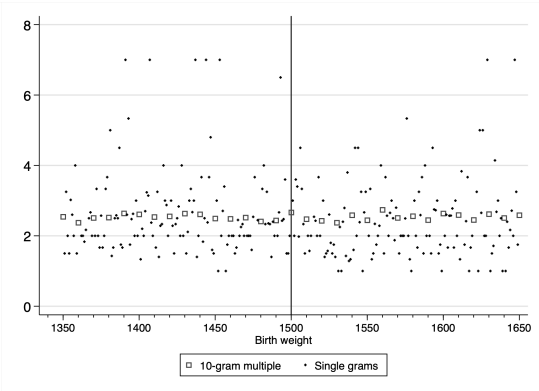
(b) Mother's occupation around 1500g



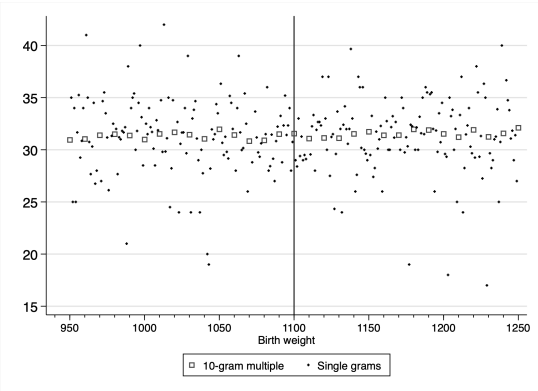
(c) Father's occupation around 1100g



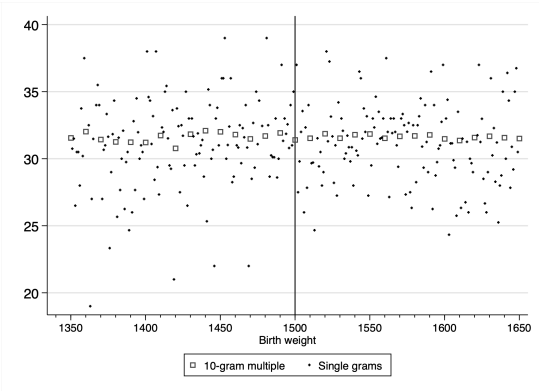
(d) Father's occupation around 1500g



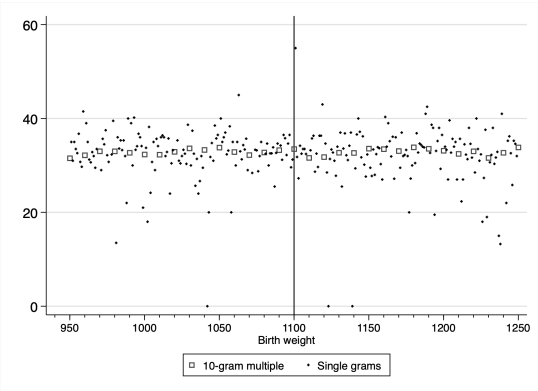
(e) Mother's age around 1100g



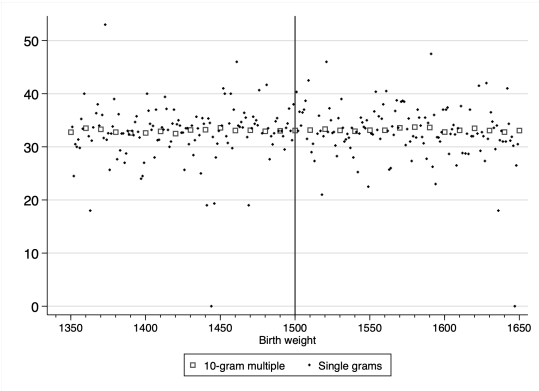
(f) Mother's age around 1500g



(g) Father's age around 1100g



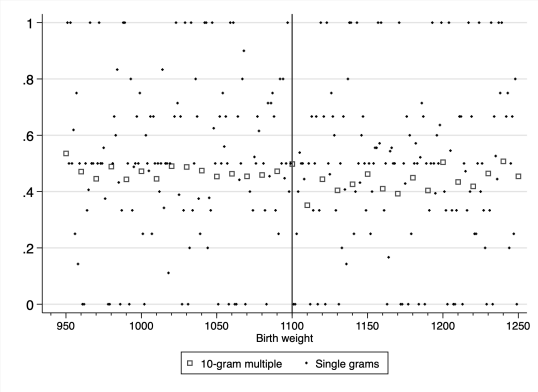
(h) Father's age around 1500g



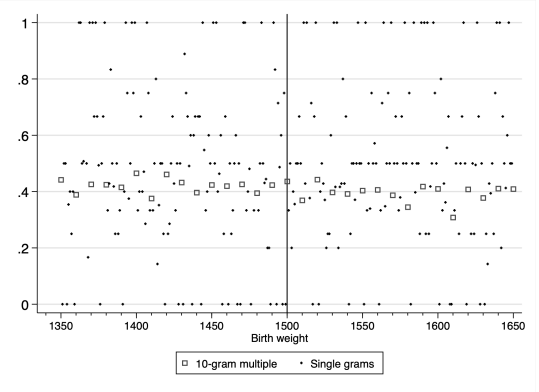
Notes: Figures plotting the average value of each variable for 10 grams multiple and single grams bins.

Figure 3.5: Bin Mean Values of Birth Characteristics

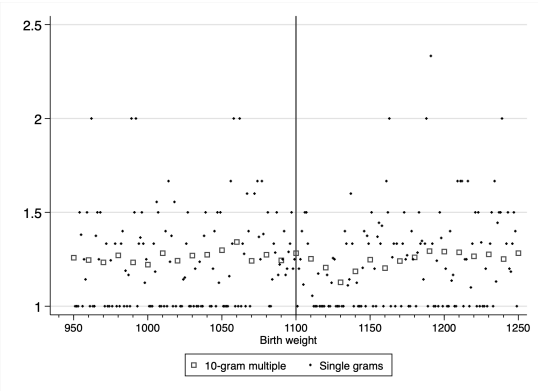
(a) Complications around 1100g



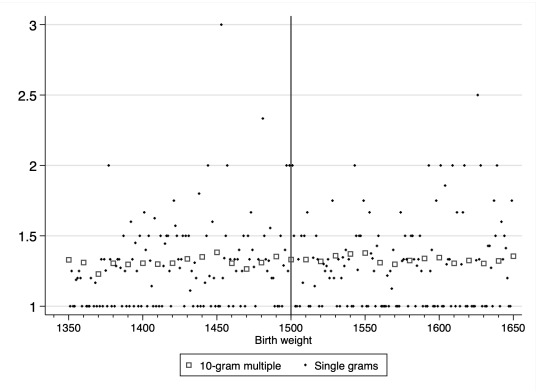
(b) Complications around 1500g



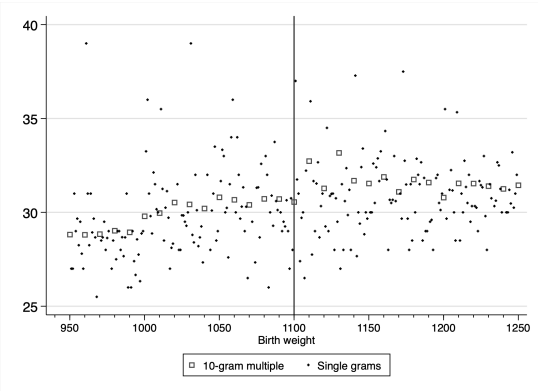
(c) Multiple delivery around 1100g



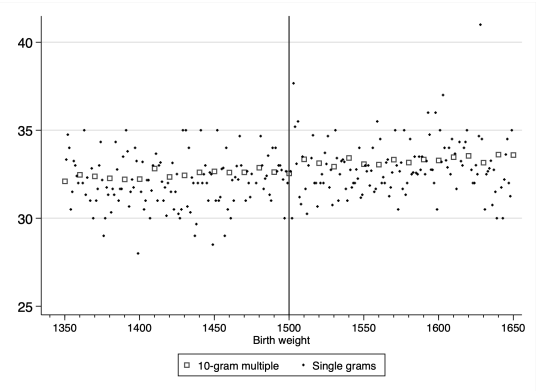
(d) Multiple delivery around 1500g



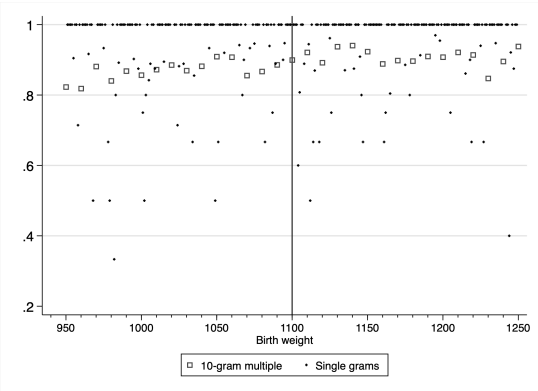
(e) Gestational weeks around 1100g



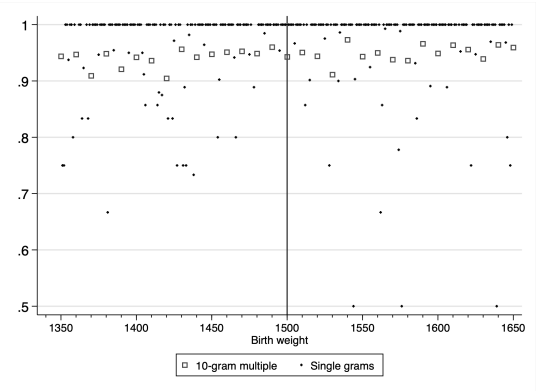
(f) Gestational weeks around 1500g



(g) Alive after 24h around 1100g



(h) Alive after 24h around 1500g



Notes: Figures plotting the average value of each variable for 10 grams multiple and single grams bins.