EARLY CAREER, LIFE-CYCLE CHOICES, AND GENDER *

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Abstract:

Do early labor market experiences determine longer-run life and career outcomes, and do they operate differentially for males and females? We study this question in the context of the physician labor market by exploiting a randomized lottery that determines the sorting of Danish physicians into internships, where students with bad lottery numbers end up assigned to less desirable local labor markets and entry-level jobs. Using administrative data that span up to ten years after physicians' graduations, we study key decisions that determine their longer-run life trajectories. We find causal effects of early-career labor market sorting on a range of life-cycle outcomes that cascade from longer-run labor market sorting, to human capital accumulation, to occupational choice, and even to fertility. Notably, we find that the persistent longer-run effects are entirely driven by females, whereas males experience only temporary career disruptions from unfavorable early-stage sorting. The gender divergence is unlikely to be explained by preferences over entry-level markets, but differential family obligations, and mentorship appear to play operative roles. Our findings have implications for policies aiming at outcome-based gender equality, as they reveal how persistent gaps can arise even in an institutionally gender-neutral setting with early-stage equality of opportunity.

* We thank Julie Cullen, Gordon Dahl, Karthik Muralidharan, Tom Vogl, and seminar participants at UCSD, University of Copenhagen, Berlin Applied Micro Seminar, and the NBER Summer Institute Gender in the Economy Meeting for helpful comments and discussions. We thank the Danish Health Authority, the Regional Councils for Physicians' Post-Graduate Education, and Dansk Telemedicin A/S for data access and helpful institutional knowledge. Fadlon (corresponding author): University of California, San Diego, Department of Economics, and NBER, 9500 Gilman Drive #0508, La Jolla, CA 92093-0508, fadlon@ucsd.edu; Lyngse: University of Copenhagen, Department of Economics, and Center for Economic Behavior and Inequality (CEBI), fpl@econ.ku.dk; Nielsen: University of Copenhagen, Department of Economics, and CEBI, thn@econ.ku.dk. We gratefully acknowledge funding from the Danish Independent Research Fund (grant no. 9061-00035B). The activities of CEBI are financed by the Danish National Research Foundation.

1. Introduction

A long tradition of economic research has studied and documented gender inequality in economic life-cycle outcomes, including human capital accumulation, field-of-study, occupational choice, and career trajectories. Recent empirical work has made great strides in understanding the underlying channels of these inequalities and in identifying causal routes by which gender disparities evolve and perpetuate. Labor economics extensively highlights the early career stage as an important potential determinant of life-cycle trajectories. Hence, early career experiences and choices could play a role in initiating longer-run gender inequalities.

Our research question is therefore: do early labor market experiences causally determine longer-run life and career choices, and do they operate differentially for males and females? Answering this question is challenging for two main reasons. First, it requires a clean source of exogenous variation in individuals' early-career choices. Second, it requires data on the evolution of a range of life-cycle outcomes and choices.

In this paper, we address this question by studying the labor market for physicians, which is an important market for highly-specialized labor in modern developed economies that has served as a "laboratory" for a range of economic questions.[1] Specifically, we study the allocation of Danish physicians to entry-level labor market positions, which offers several advantages. First, medical internship placements—i.e., physicians' first jobs—are governed by a randomized lottery that provides a clean source of variation in entry-level labor market sorting.[2] As we establish in our first-stage analysis, this generates large exogenous variation, so that graduating physicians with the worst lottery numbers are much more likely to sort into less desirable local labor markets and their respective positions which offer inferior training and future career opportunities (e.g., in terms of fewer high-seniority colleagues and weaker professional networks, less affiliation with teaching hospitals, and higher likelihood of locating in rural communities). Second, we exploit novel administrative data that allow us to track individuals for ten years after the draw as they make further human capital, labor market, and family decisions that determine their longer-run trajectories. Third, we can also explore the role of mechanisms that have been hypothesized in the literature, including preferences, family obligations, as well as mentorship and role models.

The summary of our findings is as follows. Early-career labor market sorting has far-reaching causal effects on life-cycle outcomes. While males and females with unfavorable lottery numbers are subject to similar quasi-experimental treatment, the persistent longer-run effects on all margins are entirely driven by females, whereas lottery-unlucky males experience only transitory career disruptions. We show

[1] This market has been studied since the work of Friedman and Kuznets (1954) and Arrow (1963), and recent work in this setting that is particular to gender includes Sarsons (2019), Wasserman (2019), and Zeltzer (2020).
[2] The internships typically last 1-1.5 years.

that this gender divergence cannot be explained by preferences over entry-level labor markets, and we find supportive evidence for family obligations, attitudes toward competition, and same-gender role models as potential operative channels. Overall, the findings reveal that persistent gender inequality can still appear even in a context of a highly-skilled merit-based profession with institutional early-stage equality of opportunity.

In the main part of our analysis, we investigate three categories of outcomes: geographical location and local labor markets, human capital investment and occupational choice, and family formation and fertility. We define our treatment group to be physicians with the worst lottery numbers and the control group to be physicians with the best lottery numbers,[3] and we study the long run effects of the lottery on these outcomes based on this simple design. First, motivated by the literature on the importance of location, we study the household's longer-run decision of geographical sorting. This choice affects the local labor market in which the household operates and the available career opportunities it offers, as well as the amenities available to the household. We find that the lottery has a significant persistent effect on this choice, so that by the end of our analysis window individuals in the treatment group are 6.5 percentage points (pp) more likely to sort into the less desirable local labor markets (on a counterfactual of 16 pp). We then show a clear gender asymmetry: although males and females experience similar geographical sorting effects in the internship period due to the lottery, women bear the entire long-run effect with a 9.8 pp increase in the propensity to locate in undesirable local labor markets (on a counterfactual of 14 pp). Among other dimensions, the less desirable labor markets women sort into are more likely rural, are less competitive as measured by the concentration of peer physicians, and are characterized by lower levels of skill and prestige as measured by the concentration of high-skilled senior colleagues.

Second, we move on to studying further educational investments and occupational choices. The further human capital investment that is most relevant in our setting is obtaining a medical PhD. This choice represents an occupational choice of a research career and provides access to economically more favorable and prestigious positions, such as in university hospitals. While males do not have any adverse effects from the treatment, treated females are 25 percent less likely to make this investment (5.4 pp decrease on a counterfactual of 21.3 pp). This impact alone can account for one-fifth of the observed gender-biased sorting into scientific careers (as opposed to clinical positions) among physicians in our sample. Furthermore, studying sorting into gender-represented occupations, we find no effect on men, but that treated women are more likely to sort into female-represented medical specialties, which we show to be economically less favorable.

[3] These correspond to physicians with lottery percentile ranks at the top 30% (worst numbers) and at the bottom 30% (best numbers) in our main estimations, with appropriate robustness analysis across the percentile range and estimations with linear specifications in lottery percentile ranks in the appendix.

Third, as the post-graduation stage represents a formative period regarding family choices, we analyze how early careers can affect family formation and fertility. We split the sample based on individuals' partnership status at the baseline pre-period—i.e., individuals who were partnered and individuals who were not—since the two groups enter this stage with a different set of operative family-related margins. Interestingly, among the sample of unpartnered graduates we find long-run effects on fertility. With no effects on men, women in the treatment group exhibit an increase of 11.5 percent in their number of children. This effect stems from some increased probability of becoming a parent, but it is driven particularly by a higher fertility rate with an increase of 7.1 pp in the propensity to have more than one child on a counterfactual 45.2 pp. The lack of such an impact on partnered graduates suggests this effect may be less likely driven by an underlying shift in women's family preferences but could rather relate to differential matching in the marriage market among unpartnered graduates, for which we find some support.

In the final part of the paper, we investigate and discuss potential mechanisms for the gender divergence. First, we find that the priority rankings over entry-level markets are similar across males and females. Hence, potential differential preferences, about which there is a heated discussion in the literature as a source of gender inequality, are unlikely to provide an explanation in our setting. Second, consistent with the role of mentors and their gender, we find substantial differential exposure to same-gender role models (as proxied by high-seniority colleagues) across male and female graduates during the internship. Moreover, we show using internship exit surveys, that the quasi-experiment leads to a large decrease in the probability of being assigned a female internship mentor, and that only treated female interns rank their internship's mentorship experience and quality lower. Next, we speak to recent work which has shown that women are more likely to shy away from competition and to stop competing when they face adverse experiences. Consistent with this work, we find that treated females are more likely to sort in the long run into less competitive labor markets as measured by the concentration of physician peers. Finally, our fertility results relate to the notion that family responsibilities could hinder females' advancement in the labor market. They suggest that women may crowd out long-run career goals by becoming more oriented toward the family when faced with the adverse early career event.

Our paper relates and contributes to two strands of the literature. First, classic labor economics research has underscored the importance of early career stages in shaping long-run life-cycle trajectories. This work has considered the role of search and job mobility, human capital investments, on-the-job learning and skill accumulation, and early job and career choices (see reviews in Weiss 1986 and Rubinstein and Weiss 2006). Within this literature, a related series of papers studies the effects of entering the labor market in a recession (see von Wachter 2020 for a review).[4] We contribute to this broad line of research by providing a novel lottery-based source of idiosyncratic variation for identifying effects of early careers. The margin that we study is a pervasive characteristic of early careers as young adults sort into entry-level jobs across different local labor markets. We further provide evidence on the far-reaching impacts of early careers as they cascade to a range of life-cycle outcomes, from long-run geographical sorting, to human capital investments, to occupational choice, and to fertility.

Our second contribution is to the long-standing work on gender inequality in economic outcomes and their underlying sources (see reviews and discussions in, e.g., Bertrand 2011, Goldin 2014, Jayachandran 2015, Olivetti and Petrongolo 2016, Blau and Kahn 2017, Lundberg and Stearns 2019).[5] We contribute to this literature by revealing a new important route which is inherent in the natural course of the life-cycle—the early career—that initiates and perpetuates gender inequality and norms in long-run economic outcomes. We are also able to offer insights into the operative mechanisms that could drive the findings of gender asymmetry in the effects of early careers. Lastly, as our analysis reveals that significant gender inequality can emerge in a lottery-based setup with embedded early-stage equality of opportunity, it has important policy implications. Specifically, policies for outcome-based gender equality cannot merely rely on leveling the starting playing field, but they should also target the way in which opportunities and choices evolve in practice over the formative stage of the early career. Our analysis of mechanisms offers some initial guidance in that direction.

The rest of the paper proceeds as follows. Section 2 describes the institutional setting. Section 3 describes the data sources we use. In section 4, we set out our empirical strategy. Section 5 provides the evidence on the causal effects of early careers. We begin by describing the nature of the quasi-experimental treatment, and we then provide our main analysis of the long-run effects of early careers on life-cycle choices. Section 6 explores the anatomy of the identified treatment effects. Section 7 concludes.

[4] Among others, these important papers include Devereux (2002), Oyer (2006), Raaum and Røed (2006), Kahn (2010), Oreopoulos et al. (2012), Currie and Schwandt (2014), Altonji et al. (2016), Liu et al. (2016), Schwandt and von Wachter (2019, 2020), and Rothstein (2020).

[5] Recent important studies in this active research on underlying channels investigate the role of job search and labor market preferences, social interactions, personality characteristics, and family obligations. These include, among others, Gneezy et al. (2003), Niederle and Vesterlund (2007, 2011), Bertrand et al. (2010), Buser et al. (2014), Azmat et al. (2016), Card et al. (2016), Field et al. (2016), Azmat and Ferrer (2017), Bursztyn et al. (2017), Caliendo et al. (2017), Buser and Yuan (2019), Cai et al. (2019), Cullen and Perez-Truglia (2019), Exley and Kessler (2019), Iriberri and Rey-Biel (2019), Kleven et al. (2019a), Kleven et al. (2019b), Cheng (2020), Porter and Serra (2020), Ginther et al. (2020), Le Barbanchon et al. (forthcoming).

2. Institutional Setting and Nature of Assignment to Entry-Level Jobs

2.1. Physician Training

We begin this section by describing Danish physicians' post-graduate professional experience and training, which captures the early stages of their career. Figure 1 summarizes the timeline of this process which is broadly typical of other OECD countries.[6] Following medical school, graduating physicians begin the period of their *residency*. The residency represents a period of on-the-job training, during which physicians make pivotal human capital investments and occupational choices that determine their career paths. The initial stage of residency is the *internship*, which typically lasts 1-1.5 years. The internship represents the entry-level labor market for physicians, and it determines the initial exposure to practical knowledge and career opportunities.

Completion of the internship allows physicians to practice medicine independently, that is, without the supervision of a senior physician. Following the internship, physicians engage in a process of human capital investment and job search that will determine their later positions. In this stage, they apply for different *introductory positions*, which typically last one year each. They must complete at least one such position within their future specialty of interest. This would then qualify them to apply for a *main position* within a specific choice of medical specialty, representing the last stage of the residency whereby the choice of specialty is an absorbing state in relation to physicians' future careers. Main positions can be highly competitive and hence physicians' success in this stage is strongly affected by investments and training up to that point. Specifically, practical experience from relevant introductory positions and further academic education by obtaining a PhD degree are key determinants. In the longer run, a PhD degree will further qualify a physician for a broader set of competitive positions, such as positions at university hospitals and prestigious positions of chief specialists. Upon the completion of the residency, physicians receive their specialty license and continue on to their independent careers.

2.2. Internship: Source of Variation

The internship following medical school provides our source of variation in initial job market sorting of physicians. The program matches physicians with internship positions which are supervised by assigned mentors. The internship positions aim to provide hands-on work experience and have the physicians accumulate practical knowledge and skills through learning-by-doing. Specifically, interns accumulate professional experiences through treating patients, interacting with patients' relatives, and working with a myriad of healthcare professionals. The internship consists of bundles of half-year primary positions at hospitals followed by secondary positions at primary-care practices. By construction,

[6] For the institutional structure in EU countries, see, e.g., EU Council Directive 75/363/EEC.

internships are tied to particular geographical regions and their associated hospitals. Institutionally, the healthcare system in Denmark is broadly organized such that Danish counties (with a total of 16) represent the local healthcare market (which bears similarities to Hospital Referral Regions [HRRs] in the U.S.). We note that spatial variation in entry jobs for physicians is typical of post-graduate medical training positions in other developed countries, such as the U.S., and is a main dimension by which the training programs are categorized (see, e.g., Brotherton and Etzel 2018).

Internship positions are periodically created by the Danish National Health Authority (NHA) to accommodate all graduating students and with respect to national demand for healthcare professionals. Specifically, prior to every graduation round, the NHA requires medical schools to report how many students will graduate in that round. The NHA then guarantees to create internship positions nationally at least at that amount, where the positions are designed to distribute geographically across the local labor markets based on their size. That is, in each local labor market the NHA creates a number of positions that equals the total national amount times the relative population weight of that county out of the overall Danish population.

The key institutional feature we exploit for identification is that a *random lottery* governs the placement to internships. For every graduating cohort, a public notary performs a lottery that allocates a random number to each graduating student, which sets the ordering of the matching process for that cohort. To capture individuals' relative position in the ordering relevant to them, we rank individuals' lottery numbers relative to the lottery numbers of their entire cohort. We assign to individuals their percentile within this distribution, and we refer to it as the "lottery rank" in the analysis that follows.[7]

The exact implementation of assignment to internships based on the lottery has somewhat changed over the years, but it has been continuously designed so that a better lottery number (of a lower rank) guarantees a student a more favorable position in the allocation process. We leverage this simple yet powerful feature and pool all data periods to maximize precision. Prior to 2008 the placement process has been administered such that in its primary stage the NHA would allocate students to counties based on the order of their lottery numbers. The graduating students would compile their list of priority over all the Danish counties, and they would then be matched with their highest-ranked county among counties with remaining open positions when their time in line arrives. Later, each county would match its assigned students with the internship positions (across the county's hospitals) that were created in that round, based on student choices in the order of their initial lottery number. In 2008 when the system was digitized, the process simplified into a single combined step, where interns would make a county-hospital choice in the

[7] This normalization permits a comparison between individuals with bad lottery numbers and individuals with good lottery numbers across cohorts. In Appendix Table C.4 we provide estimations for our main outcomes that include graduation round fixed effects for robustness.

order of their lottery number from the positions available nationally. Across years, each stage of the allocation process has followed a serial dictatorship procedure. In Appendix A we discuss some potential choice and prioritization considerations that could result from the incentives embedded in these processes and we investigate how they play out in practice. While the procedural change could have potentially led to differential incentives and choices, in practice the placement system has maintained similar prioritizations and allocation patterns as we now describe which is driven by students' reluctance to intern in remote rural areas.

Nature of Placement to Internships. Important to our purposes, the motivation underlying the randomization-based placement process (see, e.g., Danish Ministry of Health 1989) has been to distribute physicians more evenly across the different parts of the country, specifically to less desirable remote rural labor markets (which is a broader concern and a common policy target across OECD countries; see, OECD 2012, Ono et al. 2014). Indeed, throughout the years geographical dispersion and relocation of graduating students have been a key dimension of variation the lottery has created across the lottery rank distribution. To see this, we first calculate for each student the distance between their municipality of residence at the time of the lottery and their municipality of the internship, which captures their "relocation distance." To put it in context, we note that graduating students reside near the major cities in which medical schools are located in Denmark (Aarhus, Copenhagen, and Odense). Hence, short relocation distances broadly imply staying in the vicinity of the urban market where the student was educated, and long relocation distances broadly imply placing in internships that are located in remote rural areas.

Panel A of Figure 2 plots a graduating student's relocation distance against the student's lottery rank (where a cohort split around 2008 is provided in Appendix Figure A.2). There are two main patterns that will help guide our analysis. First, there is a clear gradient such that the relocation distance of those with better lottery numbers (lower ranks) is significantly shorter than for those with worse lottery numbers (higher ranks). This mirrors the underlying motivation for the lottery-based system, as it reveals interns' distaste for locating in remote labor markets when they get to choose. This will guide our first-stage analysis, where we will begin by analyzing how the lottery affects interns' propensity to be geographically placed in less versus more desirable local labor markets and the entry-job related implications of that placement. As we will show, a local labor market is an informative aggregate for characterizing aspects of the internship bundle.

The persistence of location-based preferences over the years, as they are revealed through choices, can be also shown in the following way. Let us characterize the desirability of a labor market (i.e., a county) based on the average lottery rank of the interns who choose to sort into it. This captures the aggregate regularities that a market is revealed as more desirable if it is chosen by individuals with better lottery numbers (lower ranks), and a market is revealed as less desirable if it is chosen by individuals with worse lottery numbers (higher ranks). We construct these rankings for both earlier and later cohorts and compare across them in Appendix Figure A.3. Locations are effectively valued over the years to a similar extent. We use this measure of market desirability throughout our analysis that follows.

The second pattern that arises in Panel A of Figure 2 across years is the nature of the distance gradient in lottery rank. Specifically, it is non-linear with an increasing slope, such that there is a flat region in the vicinity of the best lottery ranks (lower numbers, e.g., those at the bottom 30%) and a sharp slope at the vicinity of the worst lottery numbers (higher numbers, e.g., those at the top 30%). This reflects the nature of the assignment process, showing how the lottery rank has no effect on relocation among those who choose first and has a growing effect as those who choose later run out of preferable positions.

An additional way to see this feature more directly takes advantage of the rankings of local labor markets that had been solicited among the earlier cohorts as part of the allocation process. In Panel B of Figure 2 we plot individuals' pre-placement ranking of the local labor market they were assigned to in practice (where 1 is highest priority) against the percentile rank of their lottery number draw (within their graduating cohort). Reflecting the patterns we just saw above, the figure first shows that students with the best lottery ranks are effectively unrestricted in their choices. As they are the ones who make the choices first, their highest priority options are still available, and they therefore end up being assigned to their first choices. Then, as the lottery rank increases (that is, worse draws), the available choices increasingly narrow. As a result, those with the worst lottery numbers are restricted in their early career choices, and they are therefore assigned to markets that are low on their priority list. The combined patterns reflected in panels A and B of Figure 2 will therefore guide our choice of research design which we describe in Section 4. Namely, those at the lower range of lottery ranks are essentially unaffected and can serve as a natural control group, and those at the highest range of lottery ranks are the most affected and can serve as a natural treatment group.

3. Data

We combine several administrative data sources, linked by person-level identifiers, with information on all medical doctors in Denmark. We use the *Educational Registers* starting in 1980 to identify all students ever enrolled in a Danish medical school through 2017. The *Danish Authorization Register* provides us with information on all registrations of medical licenses and specializations through 2017. Our analysis population for the quasi-experiment is identified using information starting from 2001 on internship lotteries which we obtained from the Danish National Health Authority.

In addition, we use the economic administrative registers from Statistics Denmark (up to 2019). These data include administrative information on geographical location (to 2019), employers (to 2017), income (to 2017), demographics (to 2019), and education (to 2017). Notably, we are also able to link households using spousal and parent-child linkages (up to 2019). Together these data encompass a range of life-cycle choices—including career paths, occupational choice, family formation, and geographical location—which allows us to conduct a comprehensive analysis of the broad potential causal effects of early careers.

We supplement the administrative data with physicians' exit surveys, which they fill out following positions they have held. In these surveys, which are conducted by the Regional Councils for Physicians' Post-Graduate Education, interning physicians rank their workplace in a series of questions that are then clustered into topic-based categories.

4. Empirical Framework

Verification of Lottery. As the basis for our empirical analysis, we begin by establishing the validity of the lottery in terms of random assignment. In Appendix B, we run specifications that regress the graduating physicians' lottery rank on baseline characteristics available in our data. These include gender, age, an indicator for having a registered partner, number of children in the household, and high-school GPA rank. Consistent with random assignment, we find that these regressions have no predictive power, whether we test the significance of the coefficients individually or jointly. In the appendix we also run the corresponding specifications separately for males and females, with similar conclusions.

Research Design. To analyze how early career labor market sorting affects longer-run life-cycle outcomes, we employ an economically straightforward design based on the randomized lottery where we compare outcomes of a treatment group to outcomes of a control group. Specifically, we identify the dynamic causal effects of the internship lottery using the following estimating equation:

$$y_{it} = \sum_{\tau} I_{\tau} \times \alpha_{\tau} + \sum_{\tau} I_{\tau} \times Treat_i \times \beta_{\tau} + \varepsilon_{it}. \tag{1}$$

In this specification, y_{it} is the outcome of interest for individual i at time t; τ is year relative to lottery, which runs from year 0 up to year 10; I_{τ} is a vector of indicators of time relative to the lottery; and we cluster standard errors at the household level. The variable $Treat_i$ is an indicator for being in the treatment group or in the control group.

We define the treatment group to be individuals with the *worst* lottery ranks (i.e., above a certain *upper* cutoff rank), and we define the control group to be individuals with the *best* lottery ranks (i.e., below a certain *lower* cutoff rank). This is motivated by Figure 2 and it maximizes the differential treatment intensity across the differentially affected experimental groups, as it compares individuals who are most restricted in their choices to individuals who are least restricted in their choices. In constructing these groups, we need to make a choice of upper and lower lottery rank thresholds which we do in the following way. First, to keep the groups balanced with a similar size, we use symmetric thresholds from above and below. Second, we pivot the analysis around the 30% most treated and least treated (i.e., with cutoff ranks 0.3 and 0.7 as illustrated by the vertical lines in Figure 2), and we vary this bandwidth within a wide range of 20 percentage-point from 20%-40% (in analysis presented in Appendix C for the main results). This choice trades off increased power from higher treatment intensity with decreased power from reducing sample sizes, so we investigate a broad range. Our research design that compares outcomes of a treatment group to outcomes of a control group provides a standard and intuitive empirical framework, with treatment effect coefficients that are economically directly interpretable. Beyond that, it does not impose functional form assumptions on the underlying relationship between outcomes and lottery ranks (specifically, it does not use the common linear specification where linearity seems less appropriate given the patterns in Figure 2). Still, we additionally run the corresponding statistically straightforward specifications that are linear in lottery rank (which capture average changes per percentile rank point; see Appendix C).

Our parameters of interest are β_τ from equation (1), which estimate the dynamic causal effects of the lottery treatment over a course of ten years. They capture the difference at each period τ following graduation between doctors who are unlucky and doctors who are lucky in terms of the lottery draw. Given our research design, the "treatment" is the adverse event of sorting into less desirable local labor markets and the internships they offer, as we illustrate and discuss in our first-stage analysis that follows. The first-stage effects for a particular outcome of interest (such as the internship's local labor market) are estimated using β_τ from equation (1) for the immediate periods (τ's) following the lottery. The longer-run impacts of the treatment on a given life-cycle outcome—which are the target of our study—are estimated using β_τ from equation (1) for the later periods. We summarize the average longer-run effects based on the later half of our analysis horizon (periods 6-10) using the following standard estimating equation:

$$y_{it} = \alpha + \beta \times Treat_i + \varepsilon_{it}, \qquad (2)$$

where β captures the average longer-run treatment effect.

Analysis Sample. Appendix D describes our analysis sample and provides summary statistics for our treatment and control groups. Overall, the two groups are comprised of 6,076 physicians. Their average age at the time of the lottery is about 28.5. About half have a partner at the baseline, where the average number of children is 0.26. About 60 percent are female, with 2,396 males and 3,680 females in our sample. Summary statistics that split the sample by gender are provided in the table.

5. Evidence: Causal Effects of Early Careers

5.1. First-Stage Effects at Internship Period

As a starting point, we characterize the nature of the treatment by investigating the effects of the lottery on the entry-level labor market positions doctors sort into. This treatment bundle includes aggregate characteristics of the local labor market they are allocated to and characteristics of the specific internships they are matched with. The first-stage analysis sets the basis for interpreting the long-run effects of the lottery. For ease of discussion, this subsection provides a general description of the quasi-experimental variation at the internship period among the overall sample.[8]

Based on the patterns we have seen earlier, we begin with the investigation of geographical sorting and we study the overall desirability of an intern's assigned local labor market. As discussed above, we characterize the desirability of a local labor market based on the average lottery rank of the interns who choose to sort into it. We use these rankings to partition the markets into two groups of more desirable local labor markets and less desirable local labor markets.[9] In column 1 of Table 1 we study the degree to which the lottery affects the probability of interning in a less desirable market. It shows that receiving the worst lottery ranks leads to a significant 18.4 percentage point (pp) increase in the probability of sorting into less desirable local labor markets on a counterfactual baseline of 11.6 pp.

This represents a central dimension of the quasi-experimental variation in terms of sorting into local labor markets. The desirability of the labor market is a strong predictor of some entry job dimensions that are important for early career training and opportunities.[10] We proceed to successively investigate and discuss the direct first-stage effects on characteristics which capture aspects of the quality of training, nature of exposure to knowledge and experience, and future career opportunities individuals face during the internship period. Such analysis at the individual level suitably accounts for the full variation created by the quasi-experimental allocation both across markets and across jobs within markets.

The first measure of high-quality training and favorable professional networks is based on the share of high-seniority colleagues. For this purpose, we look at established physicians (those that are at least fifteen years out of medical school) who hold a medical PhD and we calculate their share out of all established physicians within the labor market. The logic behind this measure is that doctors who hold a medical PhD tend to occupy the key positions in the field. Using this measure, we find in column 2 of Table

[8] Appendix Table E.1 reports splits by gender and shows that males and females are exposed to quasi-experimental variation of similar extent.

[9] This market partition is similar if we split locations based on the average pre-placement rankings of local labor markets using the information on students' solicited priority lists.

[10] Appendix Table E.2 illustrates this point by showing the degree to which the desirability of a local labor market is correlated with internship-related characteristics. As a supplement, we also provide in Appendix Table I.1 descriptive information from national statistics that compares less desirable and more desirable markets in terms of amenities and features of the healthcare market.

1 that unlucky lottery numbers decrease the exposure to high-seniority physicians during the internship by 59 log points. Aside from quality of training, this difference additionally captures variation in the type of role models young physicians are exposed to and mentored by in the internship setting.

Another key measure that speaks directly to the quality of training, as well as future career opportunities through exposure to practical knowledge and professional networks, is the extent of attachment to university, or teaching, hospitals. Leading teaching hospitals, which are typically located in local labor markets at the vicinity of larger urban areas, are well-known to be the institutions where skill-intensive and highly-specialized procedures are performed, state-of-the-art technologies are first adopted, and innovative medical research is conducted.[11] By definition, these hospitals aim to educate and provide the highest-quality training to new physicians. Hence, whether the internship takes place in such a hospital captures an important dimension of physicians' early careers through on-the-job training. Moreover, as key players in the medical field often work and mentor in these hospitals, it stands as a boost to the starting physicians' exposure to networks and future career opportunities. Notably, we find in column 3 of Table 1 that the quasi-experiment leads to a large effect in this context: graduating physicians in the treatment group are 40 pp less likely to intern in university hospitals.

Finally, we investigate the degree to which the lottery affects the probability that a physician interns in a rural versus an urban community. We follow the formal definitions by Statistics Denmark which are based on classifications at the level of municipalities (which are sub-divisions of counties). The urban/rural divide is frequently used in the discussion of localities more broadly and in the characterization of healthcare markets and physicians' post-graduate training more specifically.[12] We note that a locality is 61.5 pp more likely to be rural when it is located in a less desirable local labor market (as shown in Appendix Table E.2). In column 4 of Table 1 we find that receiving the worst lottery numbers increases the probability that the physician interns in a rural municipality by 8.8 pp (on a baseline of 5.4 pp).

We conclude this subsection by supplementing our analysis based on administrative registers with analysis that uses complementary data from physicians' exit surveys, which they fill out at the conclusion of positions they have held. We use these self-evaluated scores to study the impact of the lottery on the quality and nature of the entry-level job experience in categories that are relevant for our analysis. To

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[11] Using our administrative patient registers, Appendix Table E.3 illustrates this point by showing how university hospitals offer exposure to more specialties and types of procedures as well as to more advanced medical technologies (based on common measures in the literature such as the prevalence MRIs, see, e.g., Bhattacharya et al. 2013).

[12] For example, this characterization of healthcare markets in the U.S. is structurally embedded in the operation of Medicare and its pricing schemes (see, e.g., Sloan and Edmunds 2012). Additionally, geographic imbalances in the form of physician degree of concentration in rural versus urban areas are a pervasive phenomenon across the developed world, and countries have taken several policy routes that aim to address rural shortages (see Simoens and Hurst 2006, OECD 2012, Ono et al. 2014). One example is Medicare's Health Professional Shortage Area (HPSA) Physician Bonus Program in the United States.

provide additional interpretation to these estimates, we also report the coefficients relative to a one standard deviation of a given score measure, which relates to the extent to which variation in evaluations could be attributed to the lottery treatment.

Table 2 summarizes this analysis. The table shows that in all categories, individuals with the worst lottery ranks are assigned during the internship period with workplaces that are ranked meaningfully lower as compared to individuals with the best lottery ranks. This includes the following categories: (1) overall evaluation of professional training and educational development; (2) work climate, which covers assessments related to the work environment and professionalism in peer interactions, the workplace's openness to interns inquiring and asking questions, as well as collaborations and sense of community; and (3) mentorship and advising, which covers evaluations regarding the construction of a training plan, frequency of follow-ups, and ongoing provision of feedback and advising related to professional and career development. We refer to splits by gender for the survey responses later, as they become relevant for the investigation of potential mechanisms that could explain the longer-run results.

5.2. Long-Run Effects on Life-Cycle Choices

We now turn to our main analysis and investigate how the internship lottery affects life-cycle choices up to ten years after the draw. We divide the longer-run analysis into three categories of household decisions: (1) location and local labor markets; (2) human capital investment and occupational choice; and (3) household formation and fertility.

5.2.1. Geographical Sorting

We begin by studying the household's longer-run decision of geographical sorting. The choice of geographical location directly affects the local labor market in which the household operates, with its associated career opportunities, and it also influences the amenities available to the family. Indeed, geographical location has emerged as an important determinant of life-cycle outcomes, from education, to economic well-being, to intergenerational mobility, to health.[13] As in our setting in which location is directly related to internship placements (which is typical of medical training jobs in other developed countries such as the U.S.; see, e.g., Brotherton and Etzel 2018), studying this household outcome is applicable more generally to natural settings where entry-level jobs geographically spread out.

We extend our analysis of the probability of sorting into differentially desirable local labor markets to our entire analysis window. Figure 3 illustrates the dynamic effects of the lottery. It plots the β_τ estimates from equation (1) for periods 0 to 10, along with their 95-percent confidence intervals. The x-axis denotes

[13] See, for example, Chetty and Hendren (2018a,b) and Finkelstein et al. (2016) for the U.S. In our Danish setting studies include, among others, Damm and Dustmann (2014), Kjærulff et al. (2015), Laird and Nielsen (2016), and Eckert et al. (2019).

the year relative to the lottery, and the y-axis denotes the effect on this outcome. As illustrated in the figure, recall that the early years capture the first-stage effect on the internship placement, and the later years capture our main empirical target of the longer-run impact on households' decisions.

Figure 3 first replicates our results from the previous subsection, showing how the internship lottery leads to a large increase in the probability of interning in less desirable healthcare labor markets. This is displayed by period 1 which is the period where the internship placement is in full effect. Notably, the figure then reveals that the lottery has important lingering effects that persist in the long run throughout the analysis window. Ten years after the lottery, individuals in the treatment group are 6.5 pp more likely to sort into less desirable local labor markets relative to a counterfactual of 16 pp.

Next, as we split the sample by gender, an important asymmetry unfolds. The figure reveals that while both males and females have similar sorting patterns at the internship period, the long-run effect is entirely driven by women. While males do not display effects in the long run, females display a 9.8 pp increase in the propensity to sort into less desirable local labor markets (on a counterfactual of 14 pp).[14]

We continue by some additional characterization of the labor markets physicians sort into in the long run. As a measure that could capture prestige and skill concentration of a healthcare local labor market, we look at the relative concentration of high-seniority colleagues. Specifically, we use our measure of the market's share of certified physicians who hold a medical PhD, who, as we mentioned above, tend to hold the high-ranked positions in the medical field. Based on equation (2), panel A of Table 3 shows a longer run effect of 6.5 log points. With no detectable effect on men, there is an effect of 9.6 log points on the local labor markets women sort to in the longer run.

Another measure that we investigate, in panel B of Table 3, considers a locality's competitiveness and desirability based on the relative concertation of physician peers. To narrow in on competition most directly relevant to the locality in which a physician likely operates, we characterize peer concentration within commuting zones. We define peers as doctors from an individual's own and adjacent cohorts, and we normalize their count by the region's population. We find a long-run average effect of the lottery driven by women, who operate in markets in which the concentration of peers is 6.3 log points lower.

5.2.2. Human Capital Formation and Career Choices

The time horizon of our analysis represents a pivotal period for longer-run career-defining choices. These include human capital accumulation through graduate education, as well as occupational and career-track choices.

[14] We find similar patterns when we consider the worst quartile of least desirable local labor markets, see Appendix Figure C.1.

Human Capital Investment: Graduate-Level Education. We first study a classic human capital investment of obtaining a medical PhD, which also represents an occupational choice of a scientific research career. This human capital choice stands as an important upward career move, as it provides access to economically more favorable and prestigious positions (e.g., in university hospitals).[15]

Table 4 studies as an outcome an indicator for the completion of medical PhD and correspondingly sorting into a scientific track. It provides estimates for β_τ using equation (1), starting from after year 5 which is when PhD completion begins to materialize following graduation from medical school. Column 1 provides the estimates for the full sample, and columns 2 and 3 provide estimates for males and females, respectively. The results reveal a clear divergence. Males do not have any adverse effects as a result of the treatment. However, females in the treatment group have significantly lower propensity to make this human capital investment, with an average longer-run decrease of 3.25 pp on a counterfactual of 11.2 pp. By the end of our analysis period, women's lower investment rate amounts to a large negative treatment effect of 5.4 pp in obtaining a PhD (on a counterfactual of 21.3 pp).

Our findings directly relate to gender-biased sorting into scientific careers, with gender inequality in science being a well-known phenomenon in the developed world (see, e.g., Holman et al. 2018, Huang et al. 2020). In our setting, the male-female gap in holding a PhD in period 10 is 8.23 pp. This implies that the treatment effect increases the gap by 25 percent, and that it can account for 20 percent of the observed gap.[16] Notably, these large effects are attributed to variation in the short internship period alone (out of the lengthy training process of becoming a physician), underscoring just how important experiences at the very early career could be over the course of the life-cycle.

As key positions in the medical field are attached to university hospitals and tend to be held by medical PhDs, a related result pertains to physicians' affiliation with university hospital in the long run as a function of our quasi-experimental variation.[17] Panel A of Table 5 summarizes these results, showing that consistent with our findings so far, there are no effects on males but there are meaningful adverse effects on women in the treatment group.

Gender-Represented Specialties. We further investigate the differential occupational choice that could reinforce gender norms by studying sorting into gender-represented occupations. We classify medical specialties—which represent "occupations" in our setting—based on the share of females within a specialty relative to their overall proportion. "Female-represented specialties" are defined as specialties with female

[15] Based on the register data, Appendix Figure F.1 illustrates within our setting the association of obtaining a PhD with early lifetime investments, in terms of foregone income, and with high returns later in the life-cycle.

[16] These assessments assume that only individuals with the worst lottery numbers, i.e., those included in our treatment group, are adversely affected. As they compose 30 percent of the sample, our calculations are performed as follows: $0.25 = (5.42 \times 0.3)/(8.23 - 5.42 \times 0.3)$, and $0.20 = (5.42 \times 0.3)/8.23$.

[17] Appendix Figure F.2 illustrates how such affiliation with university hospitals in the long run is a strong indicator for economically favorable career trajectories.

share that is higher than this proportion, and “male-represented specialties” are defined as specialties with female share that is lower than this proportion.[18]

The quasi-experimental causal effects on this occupational choice are provided in panel B of Table 5 (which also accounts for specialization dynamics by period 10). Indeed, we find that females are more likely to sort into their gender-represented specialty, where there is no longer run effect on males. Such occupational sorting shapes physicians’ career trajectories, as medical specialty choices in the residency stage govern the field of specialty physicians can practice in the long run.

Overall, we find in this subsection that female physicians in the treatment group, as opposed to male physicians, end up forgoing important human capital investments they would otherwise engage in, and they sort into economically less desirable stereotypical career paths at higher rates than they would optimally prefer. Together, these findings show that—among the women only—adverse early working-life experiences result in important career choices and outcomes that place them on disadvantaged paths. Consequently, early career circumstances can preserve and amplify underlying structures of gender bias in the labor market.

5.2.3. Family Formation

The post-graduation and early-career stages represent formative years with respect to family formation.[19] Hence, family-related decisions and career-related choices naturally intertwine. In this section, we investigate the interplay between the labor market and the marriage market, by studying how early careers can affect family formation choices in terms of partnership and fertility.

In the analysis that follows we split our sample, based on individuals’ partnership status at the baseline pre-period, into the sub-group of individuals who were partnered (i.e., had a partner listed in the demographic registers) and those who were not. Conceptually, the two sub-samples differ with respect to the household decisions they face at the beginning of their careers. Partnered individuals enter the planning period as a joint unit of two partners who make family planning choices. Non-partnered individuals are additionally faced with a household formation choice through matching in the marriage market. We now turn to study how household related outcomes are affected by the internship lottery in the longer run.

We begin by analyzing the sample of individuals who were not partnered in the pre-period. For these individuals, partnership and fertility could both be important operative margins. Table 6 summarizes the effects on these outcomes. Panel A first studies the probability of having a partner, where we find no

[18] Plotting life-cycle income trajectories for the two classes of occupations, Appendix Figure F.3 illustrates how female-represented specialties are economically less favorable compared to male-represented specialties.

[19] See Goldin and Katz (2008) for a related discussion. In terms of age, recall that in our setting the average age of young physicians at the beginning of our quasi-experiment is 28.5.

detectable effects. That is, for both genders, the treatment and control groups are partnered in the longer run at similar rates.

However, interesting patterns arise when we move on to studying fertility choices. Panel B studies the longer-run impact of the lottery on an individual's number of children. Whereas there are no effects on men, women in treatment group exhibit an increase of 11.5 percent (=0.1422/1.2374) in the number of children in their families as a result of the internship placement variation. Panels C and D break down this result by studying the probability of having one child or more (i.e., becoming a parent) and the probability of having more than one child. The results suggest that the treatment effect is more concentrated on higher number of children: women in the treatment group are 7.1 pp more likely to have more than one child as compared to women in the control group, which amounts to an effect of 16 percent.

Appendix Table G.1 shows there are no such effects on individuals who were partnered in the pre-period. This could suggest that the effects on women, in terms of number of children, may be less likely driven by an underlying shift in family-bound preferences due to a labor market shock, but rather could be related to differential matching in the marriage market among women who were not partnered. Consistent with this conjecture, we find some evidence that the marriage patterns of pre-period unpartnered women in the treatment group could differ as a result of the lottery.[20]

The findings in this subsection of effects on family formation provide novel evidence of the far-reaching impact of early careers, as they extend to an important aspect of the life-cycle that is not immediately linked to the labor market. Moreover, they reveal how in the long run adverse events that are local to the early career may alter women's trajectories from career-enhancing choices to family-oriented considerations while not altering men's longer-run choices.

6. On the Anatomy of the Treatment Effects

We have found causal impacts on females' sorting into local labor markets, human capital investments, career choices, and family formation, in a direction that preserves and amplifies underlying structures of gender bias in the labor market. Our analysis cleanly identifies a specific source of variation—the very first periods of physicians' entry-level labor market. In that sense our paper is not targeted at explaining or decomposing observed economy-wide differences across individuals with different experiences or gender. Rather, it serves as a clean real-life laboratory that provides proof of concept for the long-run impacts of early career and how they diverge across males and females. We find far-reaching

[20] Among pre-period unpartnered women who become partnered, women in the treatment group end up in less balanced unions, with higher age gaps (in the direction of the husband) and with less assortative mating (in terms of whether both partners earn a clinical medical degree). See Appendix Table G.2.

effects on career-defining and family choices from this experiment, suggesting that, over the entire spectrum, early labor market experiences represent an important determinant of life-cycle trajectories.

In this section, we supplement our main analysis with additional discussion and characterization of the nature of the effects we have identified. We first explore candidate mechanisms, and we then discuss additional insights that relate to the study of early careers.

6.1. Mechanisms

Our first-stage analysis has described the nature of our quasi-experiment as it pertains to medical graduates of both genders and whereby males and females were exposed to similar variation in treatment. Yet, our findings consistently show important differences in the causal effects of this treatment in the long run on females as compared to males. The broad literature on gender has highlighted several potential channels that could lead to gender differences in outcomes. Guided by this literature, we discuss some key candidate channels that could be relevant in our setting. The first two recap and relate to analysis we have already presented, and for the second two we provide additional analysis below.

Family Considerations. The literature has underscored how family responsibilities could hinder females' advancement in the labor market. Our identified differential effects on family formation by gender—i.e., increases in fertility for females in the treatment group but not for males—suggest that the interaction between family-considerations and career-considerations is a potential mechanism in the long-run impacts we have uncovered. That is, our findings are consistent with the notion that women, unlike men, may crowd out long-run career goals by becoming more oriented toward the family when faced with adverse labor market events at the beginning of their working life.

Competition Aversion. We have also found that females in the treatment group (and not males) are to some extent more likely to sort in the long run into less competitive labor markets as measured by the concentration of peers. Interestingly, this finding is consistent with recent work showing that women are more likely to shy away from competition and to stop competing when they face adverse experiences.[21] This could provide one potential explanation for the diverging patterns for males and females in response to adverse early career events which has placed them on less competitive and less favorable trajectories.

Preferences over Labor Markets. There is an important discussion in the gender literature about whether gender differences in economic choices, such as college majors and occupations, stem from diverging preferences or other factors such as diverging opportunities (see, e.g., Bertrand 2020). Our application allows us to test this hypothesis in the context of physicians' preferences over local labor markets. To do so, we utilize our measure for market desirability that reveals students' preferences through

[21] See, e.g., Gneezy et al. (2003), Niederle and Vesterlund (2007, 2011), Buser et al. (2014), Azmat et al. (2016), Wasserman (2018), Iriberri and Rey-Biel (2019), Buser and Yuan (2019), and Cai et al. (2019).

their lottery-based choices. We construct these market rankings based on the average lottery rank of the interns who choose to sort into it separately for males and females and compare across them.

Figure 4 illustrates the results. Each dot represents a local labor market, where the x-axis denotes male rankings and the y-axis denotes female rankings. We plot the fitted line, as well as the 45-degree line which is the benchmark under non-differential rankings by gender. We also report the slope of the fitted line, where the benchmark of non-differential ranking is 1. Overall, the estimation is notably close to the benchmark case under the null that males and females have similar average priorities over the entry-level markets.[22] Hence, differential preferences over entry-level markets is an unlikely explanation in our setting for the diverging long-run effects.

Mentorship. Lastly, we turn to the literature that has underscored the potential role of mentors.[23] Specifically, same-gender role models have been suggested as a mechanism for gender inequalities in field-of-study and occupational choice. Even more, papers have found strong influences of the gender of role models or mentors on females, with little (to no) impact on males. With this work in mind, we investigate whether differential exposure to role models could provide an explanation in our setting.

We use several measures to explore this hypothesis with regards to the treatment period of the internship. First, we return to our earlier measure of exposure to high-seniority colleagues (as represented by the share of senior physicians who hold a medical PhD), who could represent role-model figures and potential mentors. In panel A of Table 7 we consider the first-stage treatment effect with respect to exposure to same-gender high-seniority colleagues. Whereas during the internship men and women are affected to a similar extent in terms of exposure to high-seniority colleagues overall (as shown in Appendix Table E.1), we find that there is a marked divergence in exposure to same-gender potential role models at the females' disadvantage.

Second, in the internship exit surveys, interns list the senior colleague who had been assigned to them as a direct mentor/supervisor at the internship entry job. Using these data, we find that being in the treatment group of worst lottery numbers leads to a large decline in the probability of having a female mentor (see panel B of Table 7). We also find that it leads to a large decline in the probability that the head of the educational program (i.e., the internship) is female (see panel C of Table 7).

Lastly, we use these exit-survey data to study the interns' evaluation of the mentorship they have received. As we have described earlier, this category includes questions on the supervisor's training plan, provision of feedback, and advising on professional and career development. In line with the differential

[22] We reach a similar conclusion if we instead use the information we have for a subsample about students' binding pre-placement rankings of local labor markets as reported in priority lists (see Appendix Figure A.4).
[23] See, for example, Bettinger and Long (2005), Carrell et al. (2010), Blau et al. (2010), Dennehy and Dasgupta (2017), Kofoed and mcGovney (2019), Porter and Serra (2020), and Ginther et al. (2020).

mentorship hypothesis, we find that females in the treatment group rate this aspect of the internship lower, whereas there is no detectable effect on males (see panel D of Table 7).

These findings are all in line with the notion that variation in mentorship could be an operative channel in the long-run effects we have identified. They are also consistent with the literature which have found significant effects of mentors' gender on females, with little to no effect on males.

6.2. Discussion Points

We conclude this section by discussing two additional points that offer some general insight into the analysis of early careers.

Earnings as an Insufficient Statistic. Earnings are an important aggregate that we commonly resort to in the analysis of labor market outcomes, also in the study of gender inequality (see, e.g., Goldin 2014), as it could capture variation in dimensions such as skill, education, and human capital investments. However, earnings could be insufficient, and even misleading, for studying individuals' relative position in the labor market in the analysis of early careers and other important long-run contexts more broadly due to several classic reasons. In particular, by their very nature, financial compensating differentials may mask adverse impacts on important job aspects and work attributes that are integral to the multi-dimensional bundle of jobs and careers. These include, for example, prestige, work-hours effort and temporal flexibility, and dis-amenities associated with locating in rural markets.[24] Moreover, the returns to major (lengthy) human capital investments could materialize only in the very long run, a classic analysis consideration that is commonly known as the "life-cycle bias" (Black and Devereux 2011). In our context, the returns to a medical PhD, for example, materialize on average as late as 15 years after graduation (see Appendix Figure F.1). Reflecting these different points, we illustrate the broader conceptual notion of insufficiency in Appendix Table H.1, which shows that a singular focus on earnings would have missed the significant long-run effects that we have uncovered.

In this respect, our setting offers two advantages. Primarily, we are able to study multiple aspects of career-defining and life-cycle choices which are indicative of the very long-run economic position of households. These choices are in and of themselves important economic choices that the labor economics literature, and the gender literature in particular, have been highly interested in; namely, human capital investments, labor market sorting, occupational choice, and family formation. Moreover, the nature of our

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[24] Key papers on compensating differentials in the context of non-pecuniary job attributes more generally, and their particular relevance to the study of gender more specifically, include, among others, Rosen (1986), Goldin and Katz (2011), Goldin (2014), Mas and Pallais (2017), Wiswall and Zafar (2018), Arcidiacono et al. (forthcoming), and Le Barbanchon et al. (forthcoming). In the context of job location dis-amenities, papers have found that average physician earnings can be meaningfully higher in disadvantaged/rural areas (Ono et al. 2014, Gottlieb et al. 2020), and a range of countries, including Denmark and the U.S., have policies in place that offer financial incentives to physicians who operate in such locations (Simoens and J. Hurst 2006, Ono et al. 2014).

application sets forth a revealed preference logic. Physicians with the most favorable lottery ranks (those in the control group) are effectively unrestricted, and they can always choose to follow the same paths that are taken by physicians with the most unfavorable lottery ranks. Therefore, any average causal effect on long run outcomes can be attributed to being induced by the lottery to make and bear the consequences of lower priority choices.

Policy Interactions. Many countries aim to more evenly distribute physicians across space to disperse expertise where it is needed most, specifically, in rural and disadvantaged areas that traditionally face challenges attracting physicians (Simoens and Hurst 2006; OECD 2012; Ono et al. 2014). This has direct welfare implications, since it relates to equity in access to healthcare. The current policy achieves this stated goal by allocating graduating physicians to less desirable markets at higher rates than they would otherwise choose. Perturbing these initial choices then induces some persistent relocations that favor disadvantaged areas. However, our results highlight a potential unintended cost of such policies: while inducing more equal access to healthcare, inequality is fostered on a different margin, namely, gender. Only female physicians bear the long-run allocation impact of the policy.

7. Conclusion

Using a lottery that determines Danish physicians' entry-level internships, we identify significant impacts of early labor market placements on longer-run career and life-cycle choices. These far-reaching effects encompass longer-run local labor market sorting, human capital investment, occupational choice, and family formation. We find that the long-run effects are entirely driven by females, thereby providing evidence of a novel route that initiates and perpetuates gender inequality and gender-biased labor market norms. The evidence suggests that preferences over labor markets cannot explain this gender divergence, and we find support for differential family obligations, attitude toward competition, and same-gender role models as potential operative mechanisms.

Our analysis highlights how persistent gender inequality can arise even in an institutionally equitable setting. As such, our findings imply that policies that aim to achieve outcome-based gender equality cannot only rely on leveling the starting playing field. Rather, such policies should target the ways in which these (potentially-equal) opportunities play out in practice and shape into gender-differential choices over the course of the formative period of early careers. For example, are women deterred by adverse events such that they give up on career goals and shift to more family-centered lives, whereas men do not let such events alter their planned course? If so, more directed and targeted mentoring, as one example, may allow enhancing the career success of women, as suggested by some recent important studies that provide encouraging evidence.

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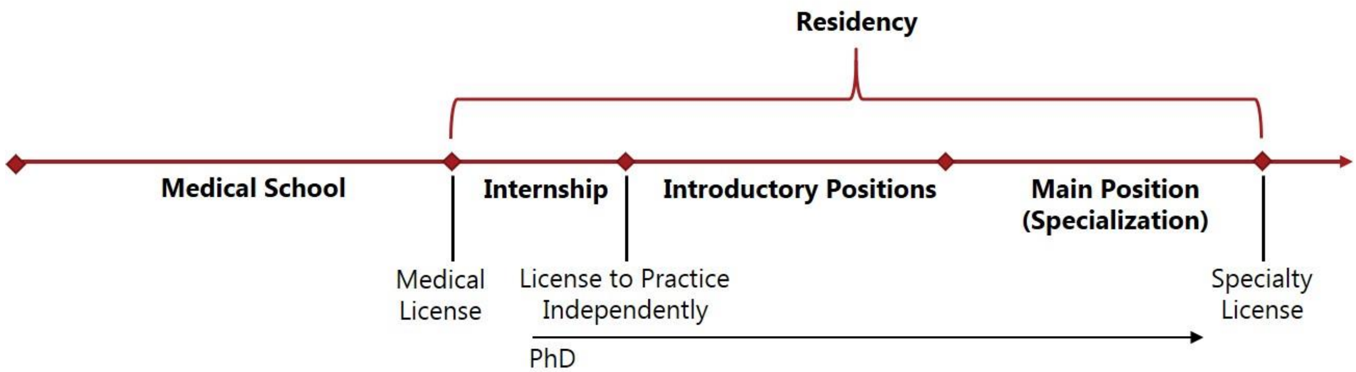
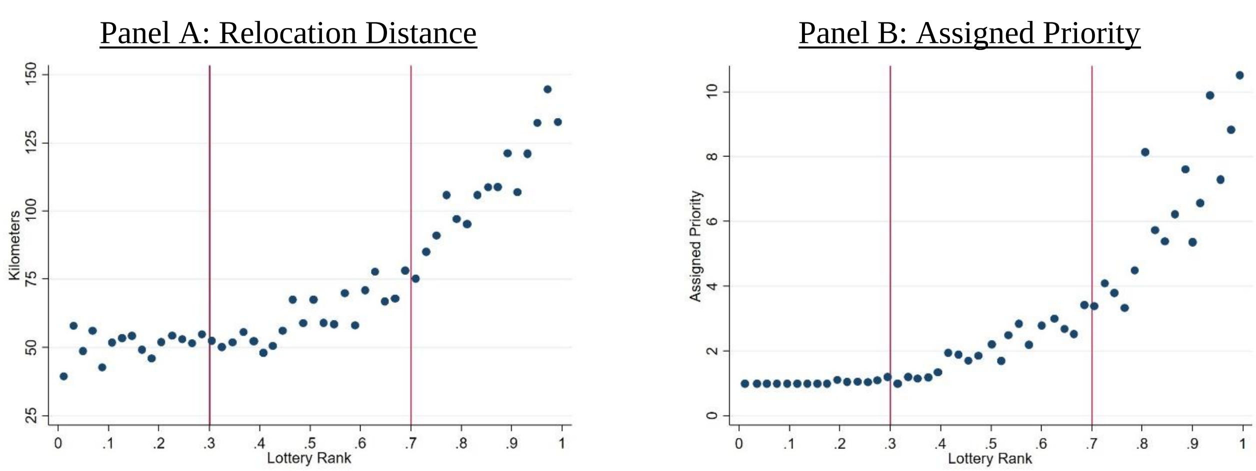
Figure 1: Timeline of Physician Training in Denmark



Notes: This figure summarizes the timeline of Danish physicians' training, which captures the early stages of their career.

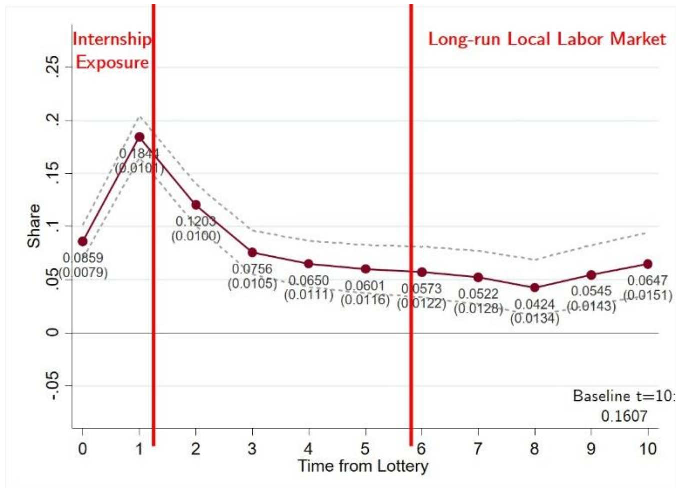
Figure 2: Nature of Placement to Internships



Notes: These figures study the nature of placement to internships. In panel A, we calculate for each student the distance between their municipality of residence at the time of the lottery and their municipality of the internship, which captures their "relocation distance." We then plot a graduating student's relocation distance against the student's lottery rank. In panel B, we use the rankings of local labor markets that had been solicited among the earlier cohorts as part of the allocation process. We plot individuals' pre-placement ranking of the local labor market they were assigned to in practice (where 1 is highest priority) against the percentile rank of their lottery number draw (within their graduating cohort).

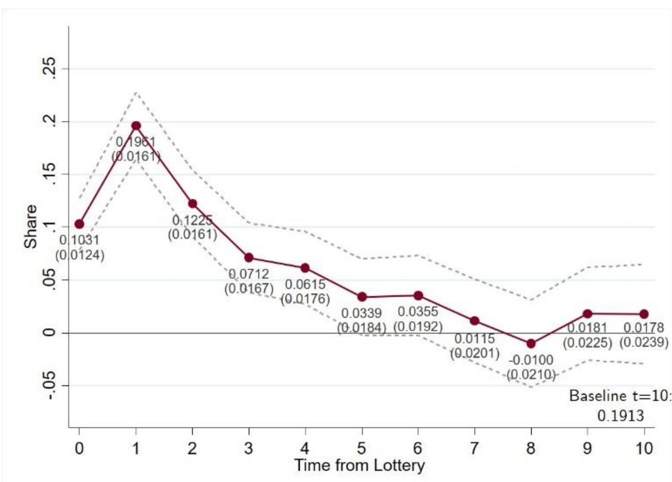
Figure 3: Effects of Early Careers on Long-Run Geographical Sorting

Panel A: Effects on Overall Sample

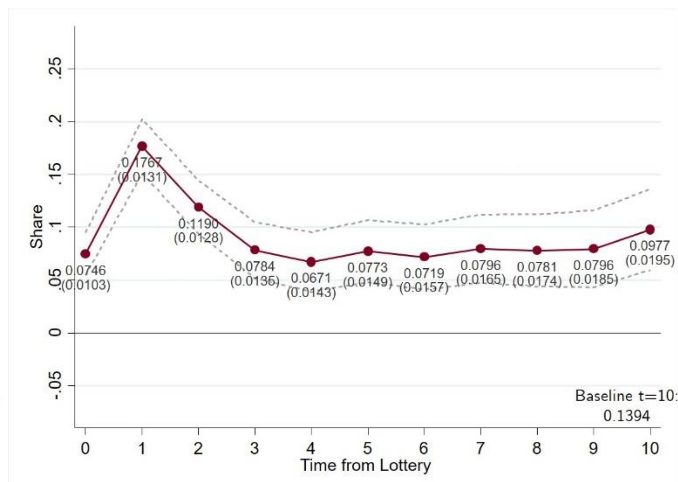


Panel B: Effects by Gender

Males

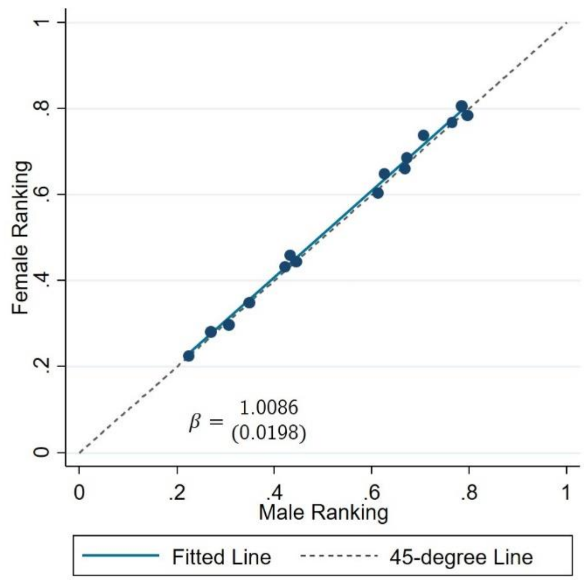


Females



Notes: This figure plots the dynamic effects of the lottery on the probability of sorting into less desirable local labor markets. We plot the β_τ estimates from equation (1) for periods 0 to 10, along with their 95-percent confidence intervals. The x-axis denotes the year relative to the lottery, and the y-axis denotes the effect on the studied outcome. As illustrated in the figure, the early years capture the first-stage effect on the internship position, and the later years capture our main empirical target of the longer-run impact on households' decisions. Panel A includes the overall sample, and panel B splits the sample by gender.

Figure 4: Preferences over Local Labor Markets by Gender



Notes: This figure compares females' and males' revealed preferences over entry-level local labor markets. We use our measure for market desirability that reveals students' preferences through their lottery-based choices. We construct these market rankings based on the average lottery rank of the interns who choose to sort into it, separately for males and females, and compare across them. Each dot represents a local labor market, where the x-axis denotes male rankings and the y-axis denotes female rankings. We plot the fitted line, as well as the 45-degree line which is the benchmark under non-differential rankings by gender. We also report the slope of the fitted line, where the benchmark of non-differential ranking is 1.

Table 1: First-Stage Effects at Internship Period

	Less Desirable Labor Market (prob.)	High-Seniority Colleagues (log)	University Hospital (prob.)	Rural Location (prob.)
	(1)	(2)	(3)	(4)
Treatment Effect	0.1844***	-0.5897***	-0.3999***	0.0883***
	(0.0101)	(0.0201)	(0.0116)	(0.0075)
Constant	0.1164***	-2.3352***	0.6280***	0.0539***
	(0.0058)	(0.0122)	(0.0088)	(0.0041)
Individuals	6,076	5,743	6,076	6,076

Notes: This table characterizes the first-stage effects of the lottery at the internship period. Column 1 studies the desirability of an intern's assigned local labor market. We characterize the desirability of a local labor market based on the average lottery rank of the interns who choose to sort into it. We use these rankings to partition the markets into two groups of more desirable local labor markets and less desirable local labor markets, and we study the degree to which the lottery affects the probability of interning in a less desirable market. Column 2 studies high-quality training and favorable professional networks based on the share of high-seniority colleagues. For this purpose, we look at established physicians (those that are at least fifteen years out of medical school) who hold a medical PhD, and we calculate their share out of all established physicians within the labor market. Column 3 studies the extent of attachment to university, or teaching, hospitals. Column 4 studies the probability that the physician interns in a rural versus urban municipality. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 2: Internship Self-Evaluations

Category		Estimate	Measure SD	Estimate/SD
Overall Evaluation	Treatment Effect	-0.4482***	1.70	-0.26
		(0.0597)		
	Constant	7.4887***		
		(0.0410)		
Work Climate	Treatment Effect	-0.5634***	2.08	-0.27
		(0.0731)		
	Constant	6.8969***		
		(0.0502)		
Mentorship and Advising	Treatment Effect	-0.3278***	1.79	-0.18
		(0.0632)		
	Constant	7.1215***		
		(0.0434)		
	Individuals	3,193		

Notes: This table uses data from physicians' exit surveys in which interning physicians rank their workplace in a series of questions that are clustered into topic-based categories. For a subsample for whom these data are available, the table studies how the lottery rank affects the quality and nature of entry-level jobs among interns based on these self-evaluated scores in categories that are relevant for our analysis. To provide additional interpretation to these estimates, we also report the coefficients relative to a one standard deviation of a given score measure, which relates to the extent to which variation in evaluations could be attributed to the lottery treatment. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: Effects of Early Careers on Long-Run Sorting into Labor Markets

	All	Males	Females
	(1)	(2)	(3)
A. High-Seniority Colleagues			
Average Treatment Effect	-0.0653***	-0.0196	-0.0964***
	(0.0151)	(0.0234)	(0.0199)
Constant	-2.0981***	-2.1232***	-2.0815***
	(0.0102)	(0.0168)	(0.0128)
Individuals	3,696	1,475	2,221
B. Concentration of Peers			
Average Treatment Effect	-0.0438***	-0.0163	-0.0627***
	(0.0101)	(0.0155)	(0.0134)
Constant	-7.5908***	-7.5967***	-7.5869***
	(0.0066)	(0.0105)	(0.0086)
Individuals	3,716	1,479	2,237

Notes: This table studies the long-run effects of the lottery on the local labor markets physicians sort into, based on equation (2). Panel A studies the share of high-seniority colleagues, and panel B studies the relative concertation of physician peers. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: Effects of Early Careers on Human Capital Investment

	All (1)	Males (2)	Females (3)
Treatment Effect at *t*			
6	-0.0052	0.0053	-0.0125*
	(0.0072)	(0.0146)	(0.0067)
7	-0.0102	0.0171	-0.0295***
	(0.0099)	(0.0186)	(0.0105)
8	-0.0168	0.0040	-0.0330**
	(0.0127)	(0.0223)	(0.0146)
9	-0.0214	0.0094	-0.0444**
	(0.0148)	(0.0251)	(0.0178)
10	-0.0275	0.0055	-0.0542***
	(0.0171)	(0.0282)	(0.0209)
Counterfactual at t = 10	0.2364	0.2697	0.2131
Average Treatment Effect	-0.0147	0.0093	-0.0325***
	(0.0096)	(0.0177)	(0.0104)
Constant	0.1359***	0.1711***	0.1121***
	(0.0069)	(0.0124)	(0.0080)
Individuals	3,857	1,551	2,306

Notes: This table studies as an outcome an indicator for the completion of medical PhD. It provides estimates for β_τ using equation (1), starting from after year 5 which is when PhD completion begins to materialize following graduation from medical school. Column 1 provides the estimates for the full sample, and columns 2 and 3 provide estimates for males and females, respectively. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Effects of Early Careers on Occupational Sorting

	All	Males	Females
A. Affiliation with University Hospitals			
Average Treatment Effect	-0.0369***	-0.0063	-0.0577***
	(0.0121)	(0.0190)	(0.0155)
Constant	0.4520***	0.4627***	0.4448***
	(0.0085)	(0.0134)	(0.0111)
Individuals	4,601	1,830	2,771
B. Gender-Represented Specialties			
	All	Males	Females
Average Treatment Effect	0.0193***	0.0065	0.0282***
	(0.0060)	(0.0092)	(0.0079)
Constant	0.0728***	0.0706***	0.0743***
	(0.0039)	(0.0063)	(0.0050)
Individuals	4,250	1,706	2,544
Treatment at t = 10	0.0369**	0.0090	0.0578***
	(0.0165)	(0.0238)	(0.0224)
Constant	0.2242***	0.1931***	0.2459***
	(0.0114)	(0.0169)	(0.0153)
Individuals	2,709	1,123	1,586

Notes: This table studies the long-run effects of the lottery on occupational sorting, based on equation (2). Panel A studies the probability of being affiliated with a university hospital, and panel B studies the probability of sorting into a physician's gender-represented specialty. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Effects of Early Careers on Family Formation—Non-Partnered Individuals

	All	Males	Females
A. Partnership			
Average Treatment Effect	0.0070	-0.0025	0.0142
	(0.0168)	(0.0242)	(0.0231)
Constant	0.7760***	0.8003***	0.7576***
	(0.0118)	(0.0168)	(0.0163)
Individuals	2,144	917	1,227
B. Number of Children	All	Males	Females
Average Treatment Effect	0.0807*	-0.0001	0.1422***
	(0.0415)	(0.0630)	(0.0549)
Constant	1.2077***	1.1685***	1.2374***
	(0.0293)	(0.0449)	(0.0387)
Individuals	2,148	919	1,229
C. One Child or More	All	Males	Females
Average Treatment Effect	0.0351*	0.0202	0.0464*
	(0.0187)	(0.0289)	(0.0244)
Constant	0.6791***	0.6567***	0.6961***
	(0.0135)	(0.0208)	(0.0177)
Individuals	2,148	919	1,229
D. More than One Child	All	Males	Females
Average Treatment Effect	0.0331*	-0.0165	0.0709***
	(0.0194)	(0.0290)	(0.0260)
Constant	0.4411***	0.4262***	0.4524***
	(0.0138)	(0.0206)	(0.0185)
Individuals	2,148	919	1,229

Notes: This table studies the long-run effects of the lottery on family formation choices among the sample of individuals who were not partnered in the pre-period, based on equation (2). Panel A studies the probability of becoming partnered, panel B studies the number of children, panel C studies the probability of having one child or more, and panel D studies the probability of having more than one child. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Mentorship as a Potential Mechanism

	Males	Females
A. Same-Gender High-Seniority Colleagues		
Treatment Effect	-0.4801***	-0.7046***
	(0.0320)	(0.0300)
Constant	-3.0569***	-3.1541***
	(0.0189)	(0.0183)
Individuals	2,247	3,456
B. Assignment to Female Mentor		
	Males	Females
Treatment Effect	-0.1017***	-0.1189***
	(0.0286)	(0.0219)
Constant	0.4376***	0.4976***
	(0.0188)	(0.0154)
Individuals	1,177	2,016
C. Female Head of Educational Program		
	Males	Females
Treatment Effect	-0.1043***	-0.0828***
	(0.0281)	(0.0216)
Constant	0.4090***	0.4262***
	(0.0185)	(0.0152)
Individuals	1,177	2,016
D. Evaluation of Mentorship		
	Males	Females
Treatment Effect	-0.1509	-0.4264***
	(0.1019)	(0.0807)
Constant	7.0663***	7.1574***
	(0.0672)	(0.0566)
SD	1.75	1.68
Effect/SD	-0.09	-0.25
Individuals	1,177	2,016

Notes: This table investigates whether differential exposure to role models during the internship could provide an explanation for the gender differences in the quasi-experimental long-run treatment effects. Panel A studies exposure to same-gender high-seniority colleagues. Using the internship exit surveys, panel B studies the probability of being assigned a female mentor, panel C studies the probability that the head of the educational program is female, and panel D studies the interns' evaluation of the mentorship they have received. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix

Appendix A: Choice Considerations

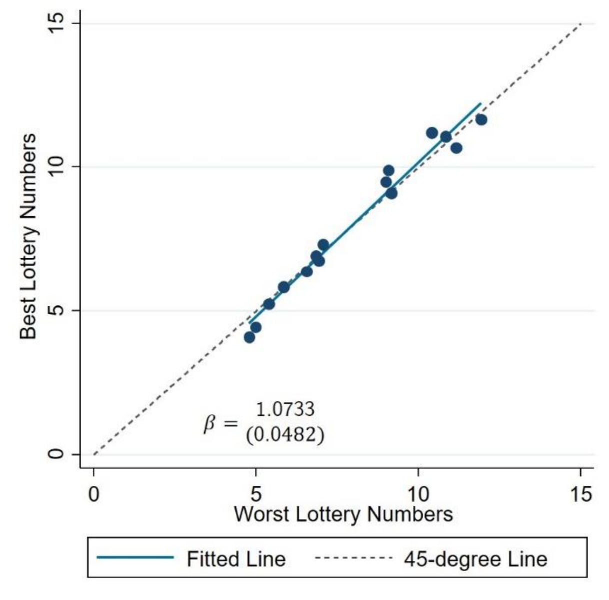
While in practice the distribution of positions across location by lottery rank display similar patterns over time, it is worth discussing some choice considerations and how they may have differed as the exact implementation of the allocation process has changed. With the structures of the matching process we describe in the text, individuals' equilibrium best-response strategy at each stage is to choose the option that maximizes their expected utility payoff, based on their individual preferences and their expectations over other students' equilibrium play. For later cohorts, this simply implies choosing their most preferred option among the options that are still available at the time they make their choice. For earlier cohorts, there are additional potential considerations to take into account. To the extent that differential job aspects within a county play a role (that is, aspects that go beyond the local labor market and its average internship-related characteristics), the process implies that at the first step of ranking counties some consideration may be given to one's place in line for making a choice. For example, it may be preferable (along some job dimension) to be first in line in a worse labor market than the last in line in a better labor market. In addition, local labor markets and the average characteristics of the jobs they offer have aspects that people may agree upon ("vertical" quality, e.g., interning in a teaching hospital) and aspects that could be individual specific (i.e., "horizontal" quality whose valuation can differ across individuals, e.g., a county's proximity to family). We now turn to explore how these choice considerations play out in practice using the information on the binding pre-placement rankings of local labor markets among earlier cohorts.

First, we consider the rankings by those with the best lottery numbers (the bottom 30%, as an example) as compared to the rankings by those with the worst lottery numbers (the top 30%). To the degree that students view their position in line for making a choice within a market as important—i.e., if dimensions of specific open jobs within a market are deemed relatively important beyond the average characteristics of the labor market itself—we would expect systematic differences in these groups' rankings over labor markets. If, on the other hand, the choice of local labor market is what dominates students' preferences regarding where to intern—due to the bundle of the entry-level job experience they offer—we would expect similarities in their overall rankings. Panel A of Appendix Figure A.1 compares the average rankings of labor markets across the two groups. Each dot represents a local market, and we plot the fitted line as well as the 45-degree line which is the benchmark under non-differential rankings. We also report the slope of the fitted line, where the benchmark null of non-differential ranking is 1. The figure is consistent with the second hypothesis, i.e., that the choice of labor market itself leads students' rankings in the first step of the allocation process. The average rankings of markets across the two groups line up around the 45-degree line, and we cannot reject the benchmark null of a coefficient of 1.

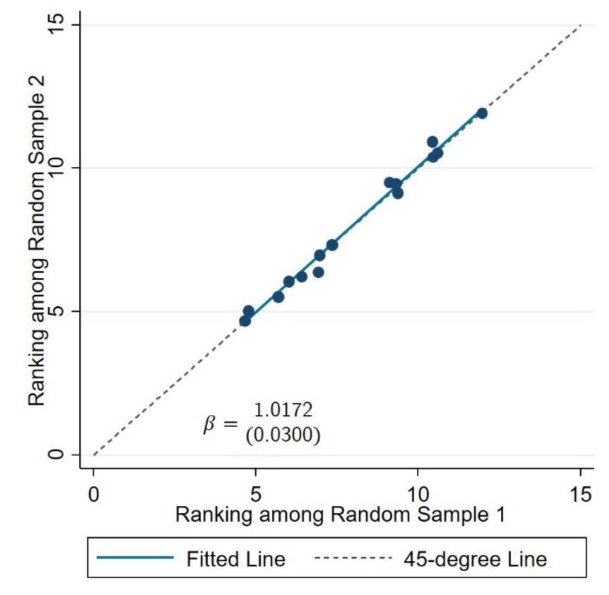
Second, we consider the degree to which the rankings of the labor markets are agreed upon among the new physicians, as compared to diverging across them due to individual specific preferences. One way to do so is to compare the rankings of labor markets across a random split of our analysis sample. If students tend to agree on the value of characteristics of labor markets, we would expect the overall average rankings of the two random subsamples to align on the 45-degree line; and if preferences are completely idiosyncratic (an extreme case), there should be no systematic relationship across the two groups' rankings. Panel B of Appendix Figure A.1 shows that the average rankings of the local labor markets across the two groups line up around the 45-degree line, and we cannot reject the benchmark null of a coefficient of 1 which represents ranking comparability. We note that while this finding suggests there is a degree of general agreement over labor market rankings across students, it does not mean there are no components of idiosyncratic preferences (over "horizontal" quality). In fact, the observation that the two groups' rankings do not perfectly align on the 45-degree is in itself an indication of the natural presence of individual specific considerations.

Appendix Figure A.1: Labor Market Rankings across Subsamples

Panel A: Best vs. Worst Lottery Numbers

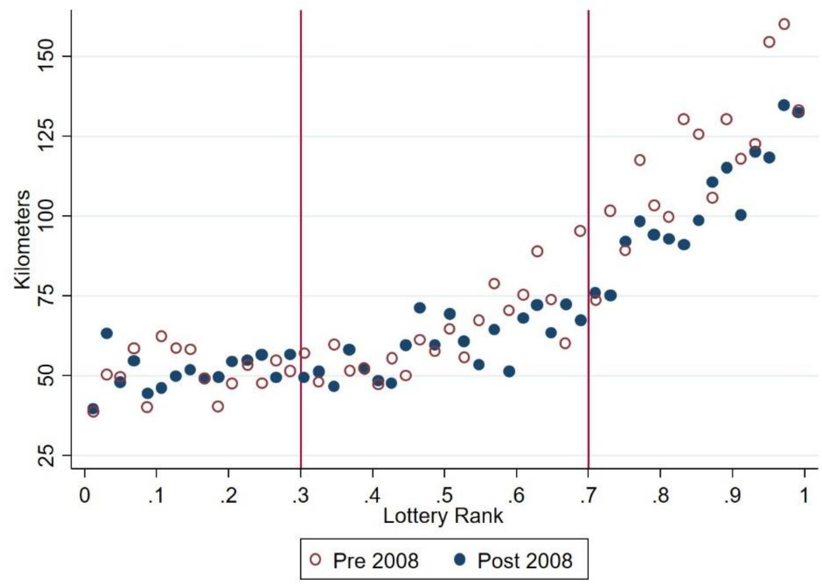


Panel B: Random Split of Analysis Sample



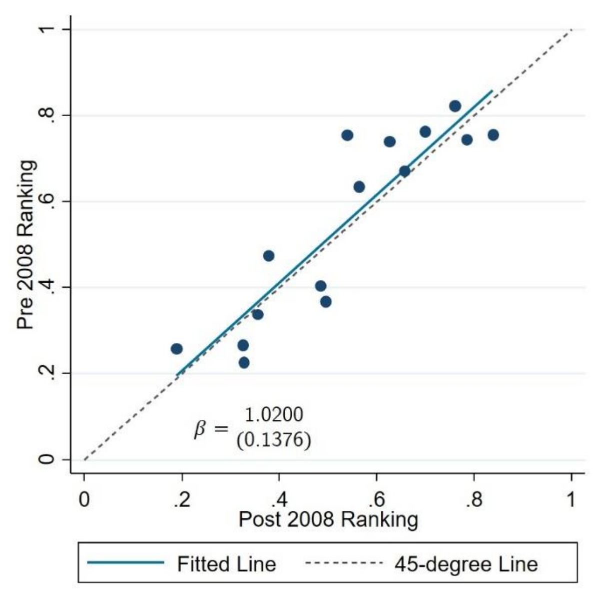
Notes: These figures compare the average rankings of local labor markets using the information on the binding pre-placement rankings of labor markets among earlier cohorts. Panel A compares the average rankings across those with the best lottery numbers (the bottom 30%) and those with the worst lottery numbers (the top 30%), and panel B compares the average rankings of labor markets across a random split of our analysis sample. In both panels, each dot represents a local market, and we plot the fitted line as well as the 45-degree line which is the benchmark under non-differential rankings. We also report the slope of the fitted line, where the benchmark null of non-differential ranking is 1.

Appendix Figure A.2: Relocation Distance



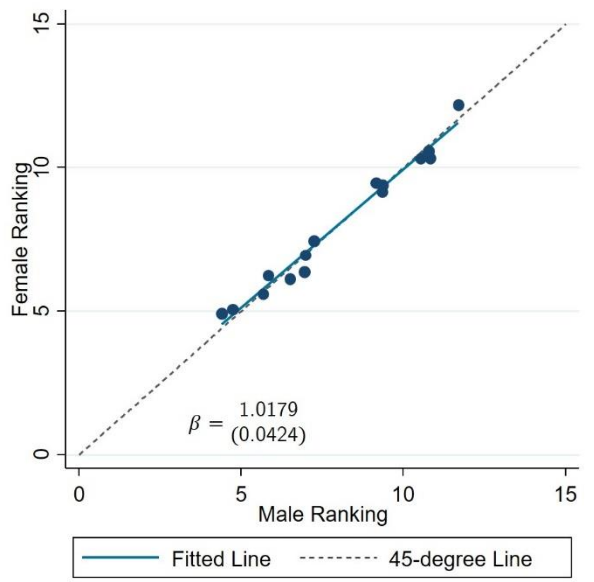
Notes: This figure plots a graduating student's relocation distance against the student's lottery rank, where we split cohorts around year 2008.

Appendix Figure A.3: Labor Market Rankings over Time



Notes: This figure compares the effective rankings of local labor markets across earlier cohorts and later cohorts. These location-based preferences, as revealed through choices, are constructed such that we characterize the desirability of a labor market (i.e., a county) based on the average lottery rank of the interns who choose to sort into it.

Appendix Figure A.4: Preferences over Local Labor Markets by Gender



Notes: This figure compares females' and males' priority rankings over entry-level local labor markets. We use the information we have for a subsample about students' binding pre-placement rankings of local labor markets as reported in priority lists. We assign to each local labor market its average priority by gender, and we then compare these priority rankings across males and females. Each dot represents a local labor market, where the x-axis denotes male rankings and the y-axis denotes female rankings. We plot the fitted line, as well as the 45-degree line which is the benchmark under non-differential rankings by gender. We also report the slope of the fitted line, where the benchmark of non-differential ranking is 1.

Appendix B: Verification of Lottery

Appendix Table A.1

	Overall Sample (1)	Males (2)	Females (3)
Gender	0.0074		
	(0.0060)		
Age	0.0004	-0.0008	0.0014
	(0.0013)	(0.0020)	(0.0018)
Partnered	0.0086	0.0084	0.0089
	(0.0063)	(0.0100)	(0.0081)
Number of Children	-0.0030	-0.0039	-0.0033
	(0.0058)	(0.0099)	(0.0073)
GPA Rank	0.0048	0.0025	0.0068
	(0.0104)	(0.0162)	(0.0136)
Observations	10,017	3,939	6,078
R-Squared	0.0004	0.0003	0.0003
F-Statistic	0.74	0.25	0.48
p-Value	0.5959	0.9082	0.7507

Notes: This table tests the validity of the lottery in terms of random assignment. We run specifications that regress the graduating physicians' lottery rank on baseline characteristics available in our data. These include gender, age, an indicator for having a registered partner, number of children in the household, and high-school GPA rank. Robust standard errors are reported in parentheses, and we also report the *p*-value of the *F*-test for the joint predictive power of the specifications we run. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix C: Research Design—Alternative Specifications

Appendix Table C.1: Sorting into Less Desirable Local Labor Markets

All

	Percentile					
	20	*25*	*30*	*35*	*40*	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0527***	0.0586***	0.0538***	0.0469***	0.0476***	0.0773***
	(0.0149)	(0.0135)	(0.0122)	(0.0114)	(0.0106)	(0.0164)
Constant	0.1710***	0.1737***	0.1689***	0.1723***	0.1699***	0.1536***
	(0.0100)	(0.0090)	(0.0082)	(0.0077)	(0.0071)	(0.0091)
Individuals	2,852	3,557	4,250	4,941	5,642	7,037

Males

	Percentile					
	20	*25*	*30*	*35*	*40*	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0107	0.0104	0.0152	0.0190	0.0236	0.0290
	(0.0229)	(0.0209)	(0.0191)	(0.0179)	(0.0167)	(0.0257)
Constant	0.1805***	0.1934***	0.1883***	0.1876***	0.1841***	0.1811***
	(0.0160)	(0.0147)	(0.0134)	(0.0125)	(0.0115)	(0.0146)
Individuals	1,138	1,436	1,706	1,948	2,230	2,798

Females

	Percentile					
	20	*25*	*30*	*35*	*40*	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0812***	0.0918***	0.0802***	0.0653***	0.0634***	0.1096***
	(0.0196)	(0.0176)	(0.0159)	(0.0147)	(0.0136)	(0.0213)
Constant	0.1645***	0.1602***	0.1558***	0.1623***	0.1606***	0.1352***
	(0.0127)	(0.0113)	(0.0103)	(0.0097)	(0.0090)	(0.0116)
Individuals	1,714	2,121	2,544	2,993	3,412	4,239

Appendix Table C.2: Human Capital Investment

All

	Percentile					
	20	*25*	*30*	*35*	*40*	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.0222*	-0.0186*	-0.0147	-0.0083	-0.0043	-0.0183
	(0.0117)	(0.0103)	(0.0096)	(0.0089)	(0.0083)	(0.0127)
Constant	0.1390***	0.1337***	0.1359***	0.1331***	0.1314***	0.1391***
	(0.0086)	(0.0075)	(0.0069)	(0.0064)	(0.0059)	(0.0075)
Individuals	2,588	3,224	3,857	4,482	5,124	6,386

Males

	Percentile					
	20	*25*	*30*	*35*	*40*	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.0021	0.0105	0.0093	0.0174	0.0177	0.0115
	(0.0219)	(0.0191)	(0.0177)	(0.0166)	(0.0153)	(0.0236)
Constant	0.1819***	0.1670***	0.1711***	0.1687***	0.1661***	0.1701***
	(0.0155)	(0.0134)	(0.0124)	(0.0114)	(0.0106)	(0.0136)
Individuals	1,040	1,304	1,551	1,770	2,027	2,538

Females

	Percentile					
	20	*25*	*30*	*35*	*40*	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.0361***	-0.0397***	-0.0325***	-0.0262***	-0.0195**	-0.0390***
	(0.0123)	(0.0110)	(0.0104)	(0.0097)	(0.0091)	(0.0136)
Constant	0.1095***	0.1106***	0.1121***	0.1095***	0.1083***	0.1185***
	(0.0096)	(0.0087)	(0.0080)	(0.0073)	(0.0067)	(0.0084)
Individuals	1,548	1,920	2,306	2,712	3,097	3,848

Appendix Table C.3: Probability of Having More than One Child among Non-Partnered Individuals

All

	Percentile					
	20	*25*	*30*	*35*	*40*	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0415*	0.0383*	0.0331*	0.0174	0.0122	0.0310
	(0.0235)	(0.0212)	(0.0194)	(0.0181)	(0.0168)	(0.0258)
Constant	0.4425***	0.4400***	0.4411***	0.4461***	0.4526***	0.4447***
	(0.0166)	(0.0150)	(0.0138)	(0.0128)	(0.0119)	(0.0149)
Individuals	1,471	1,816	2,148	2,486	2,864	3,581

Males

	Percentile					
	20	*25*	*30*	*35*	*40*	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0086	-0.0050	-0.0165	-0.0298	-0.0373	-0.0328
	(0.0357)	(0.0318)	(0.0290)	(0.0272)	(0.0253)	(0.0388)
Constant	0.4254***	0.4259***	0.4262***	0.4302***	0.4356***	0.4375***
	(0.0251)	(0.0226)	(0.0206)	(0.0195)	(0.0182)	(0.0227)
Individuals	609	775	919	1,050	1,219	1,508

Females

	Percentile					
	20	*25*	*30*	*35*	*40*	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0648**	0.0711**	0.0709***	0.0529**	0.0488**	0.0783**
	(0.0311)	(0.0282)	(0.0260)	(0.0239)	(0.0223)	(0.0343)
Constant	0.4551***	0.4506***	0.4524***	0.4579***	0.4653***	0.4496***
	(0.0222)	(0.0201)	(0.0185)	(0.0169)	(0.0158)	(0.0198)
Individuals	862	1,041	1,229	1,436	1,645	2,073

Notes: These tables investigate the robustness of our design by studying the effects on our main outcomes when we vary the percentiles that define the treatment and control groups. Columns 1-5 report estimates for long-run effects based on specification (2). Column 6 estimates a version of specification (2) that is linear in lottery rank. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix Table C.4: Effects of Early Careers on Long-Run Outcomes—Graduation Round Fixed Effects

Panel A: Sorting into Less Desirable Local Labor Markets

	All	Males	Females
	(1)	(2)	(3)
Treat	0.0538***	0.0139	0.0801***
	(0.0122)	(0.0190)	(0.0159)
Constant	0.1689***	0.1890***	0.1558***
	(0.0081)	(0.0133)	(0.0102)
Individuals	4,250	1,706	2,544

Panel B: Human Capital Investment

	All	Males	Females
	(1)	(2)	(3)
Treat	-0.0143	0.0101	-0.0312***
	(0.0096)	(0.0177)	(0.0103)
Constant	0.1357***	0.1706***	0.1114***
	(0.0069)	(0.0124)	(0.0079)
Individuals	3,857	1,551	2,306

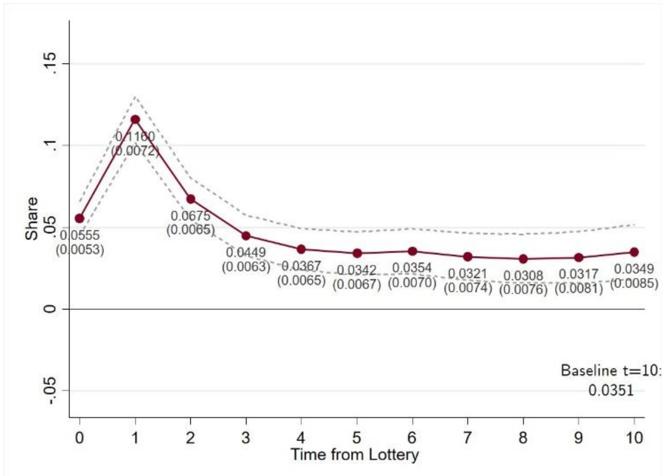
Panel C: Probability of Having More than One Child among Non-Partnered Individuals

	All	Males	Females
	(1)	(2)	(3)
Treat	0.0321*	-0.0244	0.0708***
	(0.0193)	(0.0288)	(0.0257)
Constant	0.4416***	0.4302***	0.4524***
	(0.0136)	(0.0202)	(0.0183)
Individuals	2,148	919	1,229

Notes: These tables investigate the robustness of the results for our main long-run outcomes to the inclusion of graduation round fixed effects based on specification (2). Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

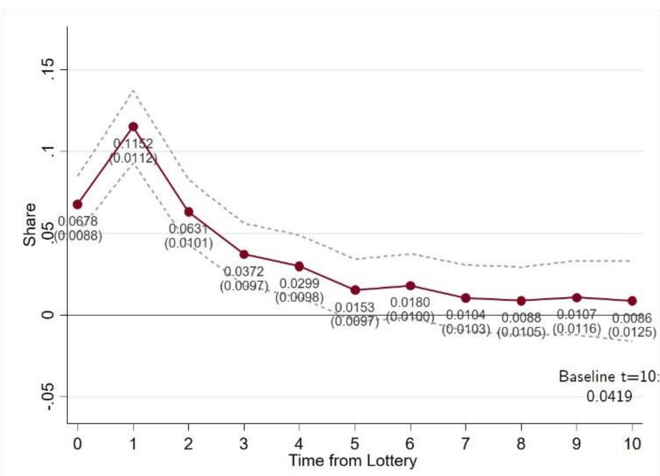
Appendix Figure C.1: Sorting into Least Desirable Local Labor Markets

Panel A: Effects on Overall Sample

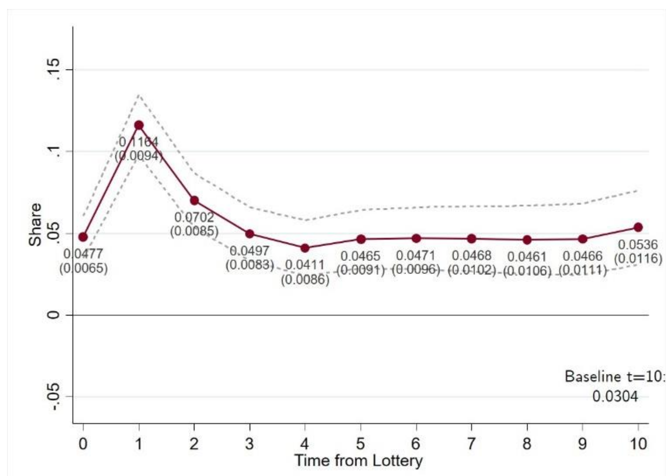


Panel B: Effects by Gender

Males



Females



Notes: This figure plots the dynamic effects of the lottery on the probability of sorting into the worst quartile of least desirable local labor markets. We plot the β_τ estimates from equation (1) for periods 0 to 10, along with their 95-percent confidence intervals. The x-axis denotes the year relative to the lottery, and the y-axis denotes the effect on the studied outcome. Panel A includes the overall sample, and panel B splits the sample by gender.

Appendix D: Analysis Sample Summary Statistics

Appendix Table D.1

	Control (1)	Treatment (2)	Difference (3)	P-Value (4)
A. Overall Sample				
Female	0.5999	0.6114	-0.0115	0.3576
Partnered	0.4964	0.5079	-0.0115	0.3700
Age	28.5096	28.5206	-0.0111	0.8606
GPA Rank	0.5021	0.5047	-0.0026	0.7246
Number of Children	0.2669	0.2644	0.0025	0.8694
Number of Individuals	3,024	3,052		
B. Males				
Partnered	0.4636	0.4696	-0.0060	0.7681
Age	28.6455	28.5995	0.0460	0.6665
GPA Rank	0.5052	0.4986	0.0066	0.5871
Number of Children	0.2280	0.2184	0.0096	0.6654
Number of Individuals	1,210	1,186		
C. Females				
Partnered	0.5182	0.5322	-0.0140	0.3964
Age	28.4190	28.4705	-0.0516	0.5047
GPA Rank	0.5000	0.5085	-0.0086	0.3652
Number of Children	0.2928	0.2935	-0.0008	0.9682
Number of Individuals	1,814	1,866		

Notes: This table provides summary statistics for the analysis sample in the year prior to the internship lottery. Panel A provides statistics for the entire sample, and panels B and C split the sample by gender. Characteristics include gender, age, an indicator for having a registered partner, number of children in the household, and high-school GPA rank. Column 1 displays means for our control group, and column 2 displays means for our treatment group. Column 3 provides the differences between column 1 and column 2. Column 4 reports the *p*-values of the test statistics (*t*-statistics for continuous variables and *z*-statistics for binary variables) of the differences in column 3.

Appendix E: First-Stage Effects at Internship Period

Appendix Table E.1: First-Stage Effects at Internship Period by Gender

	All	Males	Females
A. Less Desirable Labor Market			
Treatment Effect	0.1844***	0.1961***	0.1767***
	(0.0101)	(0.0161)	(0.0131)
Constant	0.1164***	0.1083***	0.1218***
	(0.0058)	(0.0089)	(0.0077)
Individuals	6,076	2,396	3,680
B. High-Seniority Colleagues			
Treatment Effect	-0.5897***	-0.5865***	-0.5921***
	(0.0201)	(0.0336)	(0.0250)
Constant	-2.3352***	-2.3473***	-2.3272***
	(0.0122)	(0.0202)	(0.0153)
Individuals	5,743	2,248	3,495
C. University Hospital			
Treatment Effect	-0.3999***	-0.3845***	-0.4099***
	(0.0116)	(0.0186)	(0.0149)
Constant	0.6280***	0.6223***	0.6318***
	(0.0088)	(0.0139)	(0.0113)
Individuals	6,076	2,396	3,680
D. Rural vs. Urban Locality			
Treatment Effect	0.0883***	0.0961***	0.0830***
	(0.0075)	(0.0116)	(0.0099)
Constant	0.0539***	0.0430***	0.0612***
	(0.0041)	(0.0058)	(0.0056)
Individuals	6,076	2,396	3,680

Notes: This table characterizes the first-stage effects of the lottery at the internship period by gender. Panel A studies the desirability of an intern's assigned local labor market. We characterize the desirability of a local labor market based on the average lottery rank of the interns who choose to sort into it. We use these rankings to partition the markets into two groups of more desirable local labor markets and less desirable local labor markets, and we study the degree to which the lottery affects the probability of interning in a less desirable market. Panel B studies high-quality training and favorable professional networks based on the share of high-seniority colleagues. For this purpose, we look at established physicians (those that are at least fifteen years out of medical school) who hold a medical PhD, and we calculate their share out of all established physicians within the labor market. Panel C studies the extent of attachment to university, or teaching, hospitals. Panel D studies the probability that the physician interns in a rural versus urban municipality. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix Table E.2: Characteristics of Less Desirable Local Labor Markets

	High-Seniority Colleagues (log)	University Hospital (prob.)	Rural Location (prob.)
	(1)	(2)	(3)
Less Desirable Labor Market	-0.7603***	-0.3064***	0.6153***
	(0.1737)	(0.0796)	(0.1451)
Constant	-2.5805***	0.4034***	0.0130
	(0.1268)	(0.0581)	(0.1059)

Notes: This table shows the degree to which the desirability of a local labor market is correlated with internship-related and location characteristics. * $p < .10$, ** $p < .05$, *** $p < .01$

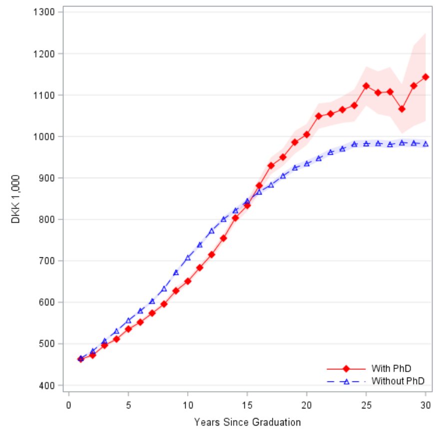
Appendix Table E.3: Features of University Hospitals

	Number of Unique Patients	Number of Admissions	Number of Specialties	Number of Procedures	Number of Unique Procedures	Having a CT Scanner	Number of CT Scans	Having an MRI Scanner	Number of MRI Scans
University Hospital	44,034***	77,639***	6.6***	35,503***	669***	0.23***	28,633**	0.41***	18,298***
	(9,326)	(17,962)	(1.7)	(9,342)	(169.2)	(0.06)	(12,332)	(0.08)	(5,870)
Constant	42,403***	82,741***	9.9***	28,947***	816***	0.75***	12,839***	0.58***	6,380***
	(5,478)	(12,223)	(1.1)	(4,283)	(95.1)	(0.06)	(2,165)	(0.07)	(1,232)

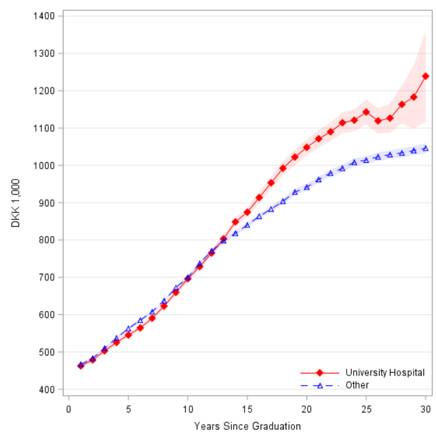
Notes: This table studies across Danish hospitals (51 in total nationally) the correlations between a series of healthcare utilization measures and a hospital being a university hospital. These measures are calculated for each hospital based on the administrative patient registers. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix F: Life-Cycle Income Trajectories

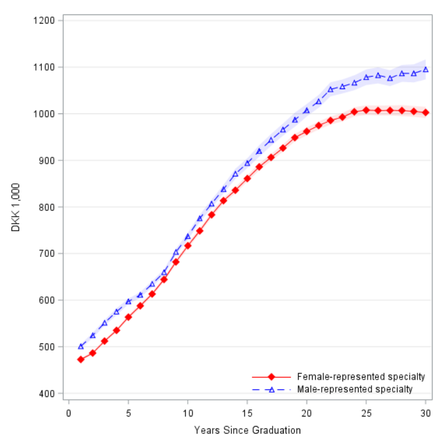
Appendix Figure F.1: Medical PhD



Appendix Figure F.2: Affiliation with University Hospitals



Appendix Figure F.3: Gender-Represented Specialties



Notes: These figures plot income paths by years since graduation for the sample of all Danish physicians. Shaded areas represent 95-percent confidence intervals. We use a comprehensive measure of income from any source, including pre-tax earnings, capital income, government transfers, and self-employment business revenues.

Appendix G: Effects of Early Careers on Family Formation Choices

Appendix Table G.1: Effects on Family Formation—Partnered Individuals

	All	Males	Females
A. Partnership			
Average Treatment Effect	0.0008	0.0153	-0.0078
	(0.0097)	(0.0145)	(0.0129)
Constant	0.9226***	0.9244***	0.9215***
	(0.0072)	(0.0114)	(0.0093)
Individuals	2,312	840	1,472
B. Number of Children	All	Males	Females
Average Treatment Effect	-0.0231	-0.0376	-0.0142
	(0.0376)	(0.0642)	(0.0464)
Constant	2.0962***	2.0891***	2.1001***
	(0.0273)	(0.0492)	(0.0324)
Individuals	2,317	844	1,473
C. One Child or More	All	Males	Females
Average Treatment Effect	0.0038	0.0221	-0.0068
	(0.0101)	(0.0172)	(0.0126)
Constant	0.9256***	0.9138***	0.9322***
	(0.0074)	(0.0133)	(0.0088)
Individuals	2,317	844	1,473
D. More than One Child	All	Males	Females
Average Treatment Effect	-0.0089	0.0093	-0.0190
	(0.0151)	(0.0254)	(0.0189)
Constant	0.8109***	0.7869***	0.8244***
	(0.0108)	(0.0188)	(0.0131)
Individuals	2,317	844	1,473

Appendix Table G.2: Marriage Market Matching Patterns among Non-Partnered Individuals

Age Gap	All	Males	Females
Average Treatment Effect	0.2830	-0.1673	0.6175**
	(0.2016)	(0.2478)	(0.2638)
Constant	0.1536	-1.5456***	1.5100***
	(0.1386)	(0.1743)	(0.1847)
Individuals	1,788	777	1,011
Assortative Matching—Medical Degree	All	Males	Females
Average Treatment Effect	-0.0337	-0.0012	-0.0619**
	(0.0250)	(0.0395)	(0.0314)
Constant	0.2942***	0.3483***	0.2502***
	(0.0181)	(0.0279)	(0.0234)
Individuals	1,490	659	831

Notes: Appendix Table G.1 studies the long-run effects of the lottery on family formation choices among the sample of individuals who were partnered in the pre-period. Appendix Table G.2 studies the marriage patterns of pre-period unpartnered individuals in terms of spousal age gap (in the direction of the partner) and assortative mating in terms of whether both partners earn a clinical medical degree. The tables report estimates based on specification (2). Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix H: Earnings as an Insufficient Statistic

Appendix Table H.1

	All	Males	Females
Earnings			
Average Treatment	6,575	11,750	1,135
	(5,425)	(9,110)	(5,802)
Constant	591,316***	664,811***	543,388***
	(3,729)	(6,355)	(3,969)
Individuals	4,195	1,674	2,521
Log Earnings			
Average Treatment	0.0142	0.0281	0.0016
	(0.0116)	(0.0195)	(0.0134)
Constant	13.2368***	13.3466***	13.1650***
	(0.0082)	(0.0144)	(0.0091)
Individuals	4,137	1,657	2,480

Notes: This table studies the longer-run effects of the lottery on earnings, based on equation (2). Earnings are winsorized at their 99th percentile. Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix I: Location Characteristics

Appendix Table I.1: Characteristics of Healthcare Local Labor Markets

		Labor Market Desirability	
		More Desirable	Less Desirable
Demographics	Population density (per sq km, levels)	1,955	91
	Population size, million (levels)	3.53	2.10
	Share 25-64 year-old with higher education	34.1	-12.3
	DI per 100	5.8	+2.0
Amenities and Norms	Home prices per square meter (DKK)	16,820	-8,861
	Annual income (DKK)	400,979	-46,242
	Revenue from income tax per capita (DKK)	39,844	-3,629
	Places in daycare per 100	43.89	-22.67
	Proportion of women elected officials	34.9	-6.4
	Expenditure on culture, sports, and leisure (per cap.)	1,680	-114
Health and Healthcare	Primary care expenditure per capita (DKK)	462	+89
	Hospital visits per capita	0.84	+0.11
	Daily smokers, %	16.2	+1.9
	CT scans	15,288	-6,245
	MRI scans	8,351	-3,904

Notes: This table provides descriptive information from national statistics that compares less desirable and more desirable counties across different amenities and features of the healthcare market. The first two characteristics are reported in averages, and the rest of the characteristics are reported as the averages for the more desirable counties and the deviation from these averages for the less desirable counties.

Appendix J: Specialty Grouping

Appendix Table J.1

Specialty	Specialty Group
Panel A: Male-Represented	
Thorax Surgery	Surgery
Orthopedic Surgery	Surgery
General Surgery	Surgery
Neurosurgery	Surgery
Internal Medicine	Internal medicine
Clinical Biochemistry	Transverse specialties
Otorhinolaryngology	Surgery
Internal Medicine: Cardiology	Internal medicine
Ophthalmology	Surgery
Vascular Surgery	Surgery
Anesthesiology	Transverse specialties
Internal Medicine: Gastroenterology and Hepatology	Internal medicine
Urology	Surgery
Panel B: Female-Represented	
Internal Medicine: Hematology	Internal medicine
Clinical Microbiology	Transverse specialties
Neuro Medicine	Other
Clinical Immunology	Transverse specialties
Clinical Physiology and Nuclear Medicine	Transverse specialties
Occupational Medicine	Other
General Medicine	General medicine
Internal Medicine: Rheumatology	Internal medicine
Internal Medicine: Pulmonary Diseases	Internal medicine
Radiology	Transverse specialties
Internal Medicine: Endocrinology	Internal medicine
Plastic Surgery	Surgery
Psychiatry	Psychiatry
Internal Medicine: Nephrology	Internal medicine
Dermato-Venerology	Other
Clinical Pharmacology	Transverse specialties
Internal Medicine: Infectious Diseases	Internal medicine
Gynecology and Obstetrics	Surgery
Pathological Anatomy and Cytology	Transverse specialties
Public Medicine	Other
Pediatrics	Other
Clinical Oncology	Other
Internal Medicine: Geriatrics	Internal medicine
Forensic medicine	Other
Clinical Genetics	Transverse specialties
Child and Youth Psychiatry	Psychiatry

Notes: This table classifies medical specialties by gender representativeness based on the share of females within a specialty relative to their overall proportion. “Female-represented specialties” are specialties with female share that is higher than this proportion, and “male-represented specialties” are specialties with female share that is lower than this proportion.