Early Labor Market Experiences and Gender Gaps in Life-Cycle Outcomes*

Itzik Fadlon, Frederik Plesner Lyngse, and Torben Heien Nielsen†

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Abstract:

Do early career experiences determine longer run life and labor market outcomes differentially for males and females? We study this fundamental question in the context of the physician labor market, a key highly-specialized market in modern developed economies. To isolate causal variation, we exploit a lottery that creates a purely randomized queue in the matching of graduating Danish physicians to their first job placements. We leverage the observation that the available choice set of internship jobs inherently differs, in terms of medical specialties and geographic locations, based on the lottery rank. Using administrative data, we investigate how the lottery affects human capital investment and other key decisions associated with career and life outcomes. Studying physicians up to ten years after graduation, we show that early labor market experiences have significant effects on females' longer run life-cycle outcomes, while males merely experience short run disruptions that quickly dissipate. Specifically, lottery "unlucky" females are 20% less likely to earn a medical PhD, which represents a meaningful decline in the rate of pursuing a research track associated with high returns; and we find no such differences for males. We show that unlucky females are instead induced to sort into lower-income female-represented medical occupations at higher rates than they would otherwise prefer. Furthermore, unlike males who are only temporarily affected during the internship, households of unlucky women are induced to settle in economically disadvantaged rural areas in the longer run. We investigate several mechanisms that could explain or mediate our findings. First, we find that male and female entry positions are generally affected equally by the lottery, suggesting the longer run gender gaps are driven by diverging paths from similar initial labor market experiences (rather than by differential entry-job preferences). Second, we find that skill (as proxied by high-school GPA) could mitigate the adverse effects on females. Third, we show evidence in support of household risk sharing and informal insurance, as households of initially-partnered unlucky females manage to attenuate the labor market shocks. We also find that wives (unlike husbands) of unlucky physicians see their own human capital accumulation delayed, pointing to another dimension of uneven burden of early life experiences via asymmetric family spillovers.

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†Fadlon: University of California, San Diego, Department of Economics, and NBER, fadlon@ucsd.edu; Lyngse: University of Copenhagen, Department of Economics, and Danish Ministry of Health, fpl@econ.ku.dk; Nielsen: University of Copenhagen, Department of Economics, Center for Economic Behavior and Inequality, thn@econ.ku.dk.

1 Introduction

A long tradition of economic research has studied and documented important gender gaps in labor market outcomes, including wages and earnings, occupational choices, and career trajectories. Recent empirical work has made important strides in understanding the underlying channels of these inequalities and in identifying causal paths by which gender gaps evolve and perpetuate. As explicit channels, such as wage discrimination and pay differentials, are becoming less prevalent or less socially acceptable, the literature has shifted to the challenging task of investigating more-intricate key routes related to attitudes, behaviors, opportunities, and choices. One such potentially important route is the role of early career experiences and initial labor market behaviors and choices, which have been extensively highlighted in classic theoretical and empirical research in labor economics as major determinants of life cycle paths.

An important open question is therefore: do early career experiences and choices causally determine longer run life and labor market outcomes differentially for males and females? Answering this key question is challenging due to two major obstacles. First, it requires a clean source of idiosyncratic variation that isolates exogenous changes to an individual's steady-state choice set. Specifically, variation that reduces choices into a sub-set and induces a switch from higher to lower ranked options, would allow identifying the differential treatment effect of choosing across these options.[1] Second, answering this question requires detailed accurate data on labor market outcomes and lifetime choices that would span a sufficiently long period, to allow for meaningful measurement of potential impacts and their horizon.

In this paper, we address this question by studying the labor market for physicians, which is a key market for highly specialized labor in modern developed economies that has served as a "laboratory" for a range of important economic questions.[2] Our analysis has several main advantages. First, in the Danish context that we study, physicians' first positions in the labor market are determined by a lottery. The lottery governs a newly-educated physician's order in making their preferred choices. As such, it directly affects the fundamental characteristics of available positions—including their medical specialty and geographic location—which provides us with a clean source of variation in individuals' early labor market experiences. Second, we construct a novel panel of Danish administrative data by combining three unique data

[1]Commonly studied business cycle shocks, for example, would be less suitable for this task since they would be confounded by their aggregate nature as we describe below.

[2]This market has been studied since the work Friedman & Kuznets (1954) and Arrow (1963), and recent work in this setting that is particular to gender gaps includes Sarsons (2019) and Zeltzer (2020).

sources from the government administrators of the lottery, the register for all medical providers, and the economic population registers. This allows us to study a range of labor market and educational choices, as well as key life outcomes including household location, formation, and marriage market aspects, as we also observe family linkages. Moreover, the data horizon spans ten years following the treatment at the exit from medical school, allowing a look into longer run effects. Together, these features provide us with a unique setting—which mimics a clean field experiment in a relevant market—to study whether and how early career behaviors and choices directly impact longer run outcomes differentially for males and females.

Our key finding is that initial experiences in the labor market have significant causal impacts on women's longer run outcomes, while men are largely unaffected. This is true despite the fact that the deck is stacked against gender asymmetries in our setting, as we study a highly egalitarian developed economy (with high female participation rate), a high-skilled merit-based profession, and a fully gender neutral policy.

We first find large effects on women's human capital investment and accumulation. Compared to female physicians who win better lottery numbers, "unlucky" women (as proxied by the latest-choosing quartile) are 5.75 percentage points less likely to obtain a medical PhD ten years after graduating from medical school. We find no such differences for males. This represents a 20% decline in females' probability to pursue a medical research track, and we show how this type of forgone investment is associated with meaningful long run financial returns. Instead, unlucky women enter—and absorb into—medical specialties earlier than they otherwise would, in the direction of more female-represented specialties which we show to be associated with persistently lower income trajectories. Finally, motivated by the vast recent work on the importance of location in determining labor market outcomes and other important aspects over the life cycle,[3] we investigate households' choice of geographic location of residence. We find that while both unlucky males and females are induced to settle and relocate in rural areas in the early career stage given their available internship options, only unlucky females display persistent significant effects of residing in rural areas in the longer run. We show how these areas are economically less favorable, specifically in terms of long run financial positions and physicians' labor market opportunities.

[3]These include educational attainment, earnings, wage growth, future income and intergenerational mobility, healthcare utilization, and mortality. See, e.g., Chetty & Hendren (2018a, 2018b) and Finkelstein et al. (2016) for the U.S., and Damm & Dustmann (2014), Kjærulff et al. (2015), Laird & Nielsen (2016), and Eckert et al. (2019) for Denmark.

We devise strategies to investigate several leading channels that could explain or underlie our findings. We first show that, for a given lottery rank, males and females are broadly equally "treated," in terms of their choice and likelihood to enter the labor market in the various possible geographic areas and specialties. This implies that the differential impacts by gender that we find are not likely explained by differential treatment intensity or initial choices in our quasi-experiment. Rather, the patterns suggest that the identified gender gaps are driven by how females and males are differentially affected by similar early career experiences, whether by making differential later-life choices or by facing diverging economic opportunities throughout their working lives. Notably, through a revealed preference logic, the nature of the setting additionally suggests that these differentials are less likely driven by gender differences in preferences and more likely driven by differences in opportunities. Within gender, the control group of lucky women can make the same choices made by the unlucky, so we should expect no treatment effect under the preference hypothesis.

Second, we do not find evidence in support of family obligations driving the results in our setting, as there are no effects on having a partner or the number of children in the household. Third, we find that skills, as proxied by high-school GPA, can serve a protective factor for unlucky females, since the long run adverse effects are concentrated among the lower skilled.

Lastly, we find novel evidence of an insurance role of the family. Consistent with the risk sharing hypothesis, exposure to differential early career experiences within an existing household unit (i.e., when having a partner prior to the lottery) strongly mitigates the adverse long run effects on females. Risk sharing within the household also appears in the form of wives (but not husbands) of unlucky physicians delaying their own human capital accumulation during the temporary period of the males' career disruption. That is, we find that the gender asymmetry in the impact of early labor market experiences extends even to the realm of family spillovers.

Our results relate and contribute to several strands of the literature. First, classic labor economics research has underscored the importance of the early career stages in shaping the long run trajectory of labor market outcomes, with 50-80% of all wage growth occurring within the first decade. This work has considered the role of market conditions, search and job mobility, human capital investments, on-the-job learning and skill accumulation, and early job and career choices (see, e.g., Topel & Ward 1992, as well as Weiss 1986 and Rubinstein & Weiss 2006 for reviews).[4] We contribute to this literature by offering a clean source of identification,

[4]Relatedly, a recent important series of papers has documented long run effects of aggregate market shocks among graduates (see, e.g., Devereux 2002, Oyer 2006, Raaum & Røed 2006, Kahn 2010, Oreopoulos et al. 2012, Altonji

based on randomized lottery, that directly varies an individual's early-career choice set (within cohorts and markets). We have the distinct opportunity to study how different entry-level positions causally affect determinants of life cycle paths, including human capital accumulation and absorbing career choices. Further, we uncover important differential effects across men and women and we are able to shed light on potential explanations.

As such, our primary contribution is to the large and long-standing literature on gender gaps in economic outcomes and their underlying sources (see discussions and surveys in, e.g., Bertrand 2011, Goldin 2014, Jayachandran 2015, Olivetti & Petrongolo 2016, and Blau & Kahn 2017). We contribute to this major literature by offering, and providing novel causal evidence for, an important route that initiates and perpetuates significant gender gaps in economic outcomes. Recent important studies in this active research have uncovered sources of gender gaps that have implications for labor market outcomes, from job search and labor market preferences, to social interactions, to personality characteristics, to family obligations.[5] The major advantage of our paper is that we show how a key classic determinant of the economic life cycle—experiences at the beginning of one's working life—can lead to significantly diverging career and life trajectories for males and females that persist in the longer run. We do so in a real-life setting that provides a well-suited field experiment in a relevant market, which offers investigation of such gender differentials even in a market for the highly skilled. Interestingly, we show that these gaps still appear in a context where initial circumstances are equalized across men and women, so that important gender gaps can perpetuate even in a "fair" playing field of early-stage equality of opportunity.

The rest of the paper proceeds as follows. Section 2 describes the institutional setting. Section 3 describes the administrative data sources we use. In section 4, we provide "first

et al. 2016, Liu 2016, and Schwandt & von Wachter 2019). The aggregate business cycle shocks studied in these papers could represent a complex bundle, and hence diverge from purely affecting a particular individual's set of labor market opportunities and choices which is our aim here. They could involve adverse financial conditions that go beyond the labor market as well as cohort or market equilibrium forces. As one example, if an occupation's overall market demand is less sensitive to economic cycles, the lack of an average effect on a graduating cohort in that occupation could mask important effects on actually varying a graduating individual's choice set. Indeed, in contrast to our individual level analysis, Chen et al. (2018) find that graduating physician cohorts in the U.S were unaffected by the Great Recession. In addition, recessionary shocks could naturally induce an inherent change in choice sets (from good times to bad times opportunities) rather than inducing variation within one's set that could allow identifying returns from steady-state choices. They could also confound estimations with the impact of induced unemployment which could have lingering effects.

[5]Among others, studies include Gneezy et al. (2003); Niederle & Vesterlund (2007); Bertrand et al. (2010); Niederle & Vesterlund (2011); Buser et al. (2014); Azmat et al. (2016); Card et al. (2016); Field et al. (2016); Azmat & Ferrer (2017); Bursztyn et al. (2017); Caliendo et al. (2017); Buser & Yuan (2019); Cai et al. (2019); Cullen & Perez-Truglia (2019); Exley & Kessler (2019); Iriberri & Rey-Biel (2019); Kleven et al. (2019a,b); Le Barbanchon et al. (2019); Porter & Serra (2020); Ginther et al. (2020).

stage" evidence on how the lottery shapes the early career stage and affects the placement to entry jobs. Then, in section 5 we provide the empirical framework for investigating longer run outcomes, and in section 6 we present our main results on gender gaps in the effects of early career experiences. Section 7 investigates potential mechanisms. Section 8 concludes.

2 Institutional Background

In this section we describe the institutional details related to the on-the-job training of physicians in Denmark which captures the early stages of their career. Panel A of Figure 1 summarizes this process which is broadly typical of other OECD countries.

Residency. Following medical school, graduating physicians begin the period of ***residency***. During this period, physicians make crucial choices of human capital investments, medical specialization, and geographic location, which are pivotal for their career tracks, job opportunities, and future positions.

The initial stage of residency, similar to the U.S. and other developed countries, is ***internships***. The internship represents the first job placement of physicians, and we use the randomization element of this program to identify variation in initial job market placements. We describe it in detail below. Completion of the internship allows physicians to practice medicine independently 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 specialty of interest. This would then qualify them to apply for a ***main position*** within a specific specialty, representing the last stage of the residency. Main positions are 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. At the end of the residency, physicians earn their specialty license and continue on to their independent careers.

Internship. The internship following medical school provides the key source of variation to identify differences in initial career experiences of physicians. The program matches physicians with a range of internship positions, which aim to provide hands-on work experience and have the physicians accumulate practical knowledge and skills through learning-by-doing. This is done by treating patients, interacting with patients' relatives, and working with a myriad of healthcare professionals. The internship consists of bundles of half-year positions at hospitals—typically under either internal medicine or surgery—followed by positions at primary care practices—typically of either general medicine or psychiatry—for a total duration of one and a half years that reduced to one year in 2007. By definition, each bundle is tied to a particular geographic location and is matched as such, a feature that will accordingly guide our empirical analysis as we describe below. The matching is done based on counties and their associated hospitals, where all university hospitals are located in urban regions. The variation across internships—in terms of location, hospitals, and medical specialties—determines the specific knowledge interns accumulate and the opportunities they face, and it therefore forms the basis for identifying the potential effects of early labor market experiences on future career paths in our application.

The key institutional feature we exploit is that a random lottery underlies the placement to internships. Based on the rank of the lottery number, which creates a purely randomized queue in the matching of physicians to their entry-level jobs, the Danish Health Authority assigns each physician to an internship. The placement process operates as follows. Twice a year all medical schools compile a list of students who are near graduation, which is provided to the National Health Authority (NHA). These students list their priority over the Danish counties (with a total of 12) in which they can choose to intern, as well as their priority over internship positions within their matched county. A public notary performs a lottery that allocates a random number to each student. The NHA allocates the students to counties based on the order of their lottery numbers, so that they are matched with their most preferred county (according to their priority list) within the remaining positions. Next, the NHA provides the counties with the list of their allocated students, and each county matches the students with internship positions based on their ranked preferences and the same lottery number. Students then begin the internship immediately following graduation from medical school.[6]

[6]The few exceptions to the process of internship placement are summarized in Appendix D.

Later Labor Market for Physicians. Licensed Danish physicians can work in either the primary care sector or the secondary care sector. The primary care sector consists of independent physician clinics, which include general practitioners and specialists. The secondary care sector consists of hospitals. These include research hospitals that are located in the vicinity of the university cities.

As a motivating starting point of our gender-based analysis, panel B of Figure 1 illustrates income paths over the life-cycle for male and female physicians. The figure shows the standard pattern by which income evolves over age for both genders, and, notably, it reveals that throughout their working lives female physicians make less income than their male counterparts. This documents a persistent gender gap in income in our setting, which seems to widen over the course of the life-cycle. These patterns of pay differences across male and female physicians are typical of other developed countries, specifically the U.S. (with even larger gender gaps) as shown by Jena et al. (2016) and Zeltzer (2020).

3 Data

We combine several administrative data sources linked via person-level identifiers to construct a unique database on Statistics Denmark's servers. Our population of interest is the combination of all authorized medical doctors, identified via the Danish Authorization Register which provides information on all medical licenses and specializations and the date of obtaining licenses from 1980-2016, and students ever enrolled in a Danish medical school from 1980-2016, identified via educational registers. From the archives in the Danish Health Authority, we compile information from the biannual lotteries from 2001-2014. There are a few lottery rounds for which data are missing from the registers (summer 2004, 2008, summer 2009, 2010, and 2011). Then, using the Danish administrative registers from Statistics Denmark up to year 2016 (inclusive), we compile a panel data set for our population. The data include information on income, place of living, workplace, demographics, and education. We are also able to link households using spousal and parent-child linkages. Together these data allow us to investigate a range of economic outcomes and choices, including career tracks through educational attainment and choice of specialty, family formation through choice of partner and number of children, and households' geographic location of residence.

In addition, we have gained complementary information on the allocation and choice of internships from 2008-2019. The data are managed by a private company, Danish Telemedicine (DT), and are located on separate servers. Along with the lottery numbers, these data contain rich details on all internship positions and placements for all graduating medical students (with a total of approximately 10,000 students over the course of this 12-year period). We use these data to investigate the quasi-experiment's "treatment" and its intensity by studying how the lottery rank determines the underlying characteristics of the initial internship position, specifically in terms of medical specialties and geographic locations.

4 Variation in Early Career

As the basis for our empirical analysis, we begin by establishing and assessing the extent of the "first stage" of the lottery and its nature. We test the validity of lottery and we then show how the lottery directly affects the placement of physicians to internships.

4.1 Verification of Lottery

We first provide analysis to test the validity of our lottery instrument in terms of random assignment. In Appendix Table B.1 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 (and whether they apply for the lottery jointly as a couple), the number of children in the household, and high-school GPA. Consistent with random assignment, we find that these regressions have no predictive power. This is the case whether or not we include lottery round fixed effects, which represents the cohort level by which the lottery is performed, and when we test the significance of the coefficients either individually or jointly. In the table we also run the corresponding specifications separately for males and females, with similar findings.

4.2 Placement to Internship

Next, we analyze the causal effects of the lottery on placement to internships with respect to location and specialty. Our focus is on geographic location since, as we describe in the institutional background, it is the procedure by which choices are ranked and assigned. Characterizations of medical internships and training programs by geographic regions and specialties are common practice; see, e.g., Brotherton & Etzel (2018) for the U.S. case. To do so, we exploit our complementary data set that comprises detailed information on the internship positions. In what follows, we characterize the resulting internship placements for each gender by lottery rank bins to explore non-parametrically the treatment intensity of the quasi-experiment.

Spatial Placement. First, we investigate the distance between the student's pre-graduation home address, when the student is drawing the lottery number, and the workplace address of the internship after having been placed.[7] We note that a high lottery number is less favorable as internships are allocated starting from the lowest to highest numbers. Panel A of Figure 2 shows the relationship between the relocation distance to the internship and the rank of the lottery number across males and females. Important for our analysis, there is a clear non-linear relationship. The luckiest percentile ends up in a position that is 30 km away from their pre-lottery home. There is a gradient of about 4 km among the luckiest 75%, so that a physician at the 75th percentile finds a position around 100 km from their pre-graduation location. The gradient is steeper and is about 23 km among the least lucky 25%, where those who draw the worst rank are placed in a position almost 250 km away from their initial location.

This pattern is consistent with the non-linearity of market clearing. For example, if there are 75 positions of a favorable internship A and 100 physicians, then the 75 physicians with the lowest lottery numbers will be unaffected, and only the placement of the 25 physicians with the worst numbers will be affected. Since location is the procedural factor by which internship bundles are allocated, we let this finding guide our empirical strategy. Accordingly, we define physicians with the highest 25% of lottery numbers as the "*unlucky*" treatment group, and we define physicians with the lowest 75% of lottery numbers as the "*lucky*" control group. We note that all Danish medical schools are located in urban areas. Hence, shorter distances broadly represent urban locations, where all teaching university hospitals are located as well, and longer distances represent more rural areas.

Specialty Placement. Second, we investigate the placement to internship medical specialties. Panel B of Figure 2 shows the relationship between the assigned specialty and the rank of the lottery number across males and females.

[7] We calculate the distance to the internship as the travel distance from the students' home address zip code to the internship hospital zip code.

Panel B.1 shows the initial position of an internship bundle, where doctors learn acute medical competences in a hospital setting. The panel reveals that most students prefer internal medicine over surgery as their internship specialty. Among the luckiest percentile, about two thirds choose internal medicine, while only less than a quarter choose surgery. For lower lottery numbers, there is a decreasing slope in the probability of being assigned to internal medicine positions of 7.6 pp. This decrease is offset by the increasing slope of surgical positions of 8.5 pp. The patterns that internal medicine is generally preferred over surgery in the internship period reflects that internal medicine specialties are more "general" and may better serve as a stepping stone towards later specialization. In that sense, surgery specialties may constrain options for later specialization as skills learned in surgery are more specialty-specific. This confirms the consensus in the medical field that to keep later career options open, one should practice internal medicine (as compared to specialties such as surgery) as it allows acquisition of general transferable skills.[8]

Panel B.2 shows the secondary position of an internship bundle, where the doctors learn skills related to continuity of patient care in a clinic setting. The panel reveals a relatively constant choice of general medicine across lottery ranks. As approximately 80% of all positions at this stage of the internship are in general medicine (so that positions are not scarce), the pattern is consistent with a preference for acquiring general knowledge. The right figure shows the sorting into psychiatry. It shows a positive slope of 8.3 pp, indicating that students are reluctant to choose psychiatry as revealed by the placements of those who choose first. Practicing psychiatry is more limiting compared to general medicine where interns see and treat patients with a variety of conditions, so the patterns are again consistent with a preference for acquiring general skills.

Overall, the results of this subsection provide three regularities. First, the lottery rank significantly affects a physician's internship position which verifies our first stage. The way in which physicians are placed to locations guides our empirical analysis which we describe next. Second, consistent with theories of optimal human capital accumulation, physicians seem to display a preference for acquiring general transferable on-the-job knowledge and skills. Third, males and females seem to display very similar placement gradients by lottery numbers. Hence, beyond the fact that the lottery and internship assignment mechanisms are gender-neutral, the

[8]We have learned of this consensus by talking to junior and senior physicians as well as public officials at the related governmental agencies and the Danish Medical Association.

variation in internship placements by lottery number does not seem to differ by gender. In other words, the "treatment" of the lottery and its intensity seem broadly similar across genders. As a result, potential differential effects of the quasi-experiment could not likely be explained by gender differences in internship choices (or preferences over internships) conditional on a lottery rank. As such, gender gaps in the effects of the lottery would be more likely driven by diverging paths and differential effects of similar variation in early career experiences, whether those are induced by later-stage choices or available opportunities. Lastly, we note that the results here also describe the nature of the first stage, or the treatment, of the lottery. Broadly, the lottery instrument exogenously induces individuals with favorable draws to be placed in internships in closer urban regions, which implies interning in teaching university hospitals, in specialties with high acquisition rate of general skills; as compared to internships in further rural areas and in more skill-specific specialties, in which individuals with less favorable draws are exogenously placed. The nature of our analysis would largely capture the average causal effects of, or the returns to, entering the first type of internship bundles as compared to the latter.

5 Empirical Framework

Research Design and Estimating Equations. To analyze how early career experiences affect life-cycle outcomes, we employ a straightforward design based on the randomized lottery. Specifically, for an analysis horizon of up to ten years post graduation, we compare the outcomes of unlucky doctors to the outcomes of lucky doctors over time. Informed by the previous section, we define the top quartile of the lottery numbers to be our *treatment* group of unlucky doctors, and we define the bottom quartiles of the lottery numbers to be our *control* group of lucky doctors. In Appendix B, we investigate the robustness of this design by studying the effects on our main longer run outcomes when we vary these percentile definitions (in Appendix Table B.2) or use a linear specification in lottery rank instead (in Appendix Table B.3), all with similar conclusions.

We estimate the dynamic and longer-run effects of the internship lottery using the following equation:

$$y_{i,t} = \sum_{\tau=0}^{10} I_\tau \times \alpha_\tau + \sum_{\tau=0}^{10} I_\tau \times Treat_i \times \beta_\tau + \varepsilon_{i,t}, \tag{1}$$

where t is calendar year and τ is year relative to lottery so that 0 is the year of the lottery. Note that the internship itself can begin in either the year of the lottery or the following year, so that period 0 is transitional. $y_{i,t}$ is the outcome of interest for individual i at time t. $Treat_i$ is an indicator for being in the treatment group of unlucky doctors. I_τ denote indicators for time since the lottery. β_τ are our parameters of interest: they estimate the quasi-experiment's treatment effects by capturing the difference across unlucky and lucky doctors at each year relative to the time of drawing the lottery number, for up to ten years.

Finally, when studying mean impacts and heterogeneity in the longer run by looking at sample splits, we use the following specification that averages over the last few periods of our analysis horizon (using years 7-10):

$$y_{i,t} = \alpha + \beta \times Treat_i + \varepsilon_{i,t}, \tag{2}$$

where β is our parameter of interest.

Analysis Sample. Appendix Table A.1 describes our analysis sample and provides summary statistics for our treatment and control groups. Overall, the sample is comprised of 5,720 physicians. Their average age at the time of the lottery is 28.5. About half have a partner at baseline, where the average number of children is 0.3. There are 2,306 males and 3,414 females in our sample. Additional summary statistics that split the sample by gender are provided in the appendix table.

6 Evidence on Gender Gaps in the Effects of Early Career Experiences on Life-Cycle Outcomes

We now turn to provide our main analysis and investigate how the internship lottery affects key economic outcomes up to ten years after the draw. First, we analyze human capital investments and career choices that determine physicians' lifetime trajectories. Then, we additionally analyze geographic location in the longer run in terms of residing in areas and operating in local labor markets that are economically disadvantaged.

6.1 Human Capital Investment and Career Paths

We begin by studying the choice of human capital accumulation, which is perhaps the most important determinant of life-cycle earning (Rubinstein & Weiss, 2006). As obtaining a PhD degree is a classic major investment choice studied in the labor economics literature, we analyze it as our main outcome. Specifically, we study the probability the new physician has entered or completed a PhD program following medical school, which translates in our context to choosing a research track that represents an important upward career move. In the medical profession in Denmark, pursuing a research track by obtaining a PhD translates to higher permanent income and qualifies a physician for more prestigious research positions at public sector hospitals, specifically at the university hospitals, and chief physician positions.[9] Panel A of Appendix Figure C.1 clearly 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.

Figure 3 provides the main result of our analysis. We construct our figures in the following way. The blue line and squares represent the counterfactual trajectory by plotting the mean outcomes for the control group of lucky physicians. The red line and circles represent the treatment effects. Specifically, we display the β_τ coefficients from equation (1), along with their 95-percent confidence intervals, by adding them up with the counterfactual levels to capture both levels and treatment effects. We also report in black the point estimates for β_τ, which equal the vertical distance between the two lines.

In Figure 3 we plot the probability of pursuing a PhD, starting from the year of the experiment to ten years after the experiment, separately for males and females. The figure first reveals no differential patterns by lottery rank for males. However, in clear contrast, we find that unlucky females are significantly less likely to invest in their professional human capital as compared to lucky females. The differential investment rate begins showing in the years after the internship, so that by the tenth year after the experiment the treatment effect amounts to a decline of 5.75 pp, which represents a decreased probability of 20% (on a counterfactual of 28.14 pp).

We provide complementary analysis to investigate what the unlucky females potentially do instead of investing in their human capital. We are particularly interested in studying whether

[9] In terms of the training process we described earlier (see panel A of Figure 1), achieving a PhD entails an important comparative advantage when applying for a main position, especially within more competitive specialties.

their search process for a main occupational position is adversely affected, as would be captured by the dynamics of residency completion, and whether it amplifies sorting into female-represented specialties, which are associated with consistently lower average life-cycle income trajectories (as illustrated in panel B of Appendix Figure C.1).[10] We note that physicians' choices of career paths in the early labor market years determine their future lifetime trajectory. Specifically, as specialist physicians can only practice within their specialty, suboptimal choices of early specialty completion are an absorbing state in terms of future labor market possibilities.

Figure 4 shows that unlucky females are indeed induced to complete residency in female-represented specialties at higher rates. They are 7 pp more likely to specialize within these specialties, while there do not seem to be detectable effects for males.

Overall, unlucky female physicians end up forgoing important human capital investments they would otherwise engage in, and they sort into financially less desirable female-stereotypical positions at higher rates than they would optimally prefer. Together, these findings show that—among women only—early working-life labor market experiences result in important career choices and outcomes that place them on disadvantaged paths of lower life-cycle income. Consequently, early career circumstances preserve and amplify underlying structures of gender bias in the labor market.

6.2 Geographic Location and Local Labor Markets

An additional aspect of life and career paths is the household choice of geographic location. It could directly affect one's local labor market and job opportunities, and it could influence the amenities available to the household. Active research has underscored the importance of geography for families' well-being and later-life outcomes, from education, to income, to intergenerational mobility, to health.[11] The link between early career experiences and longer-run geographic location choice arises in our setting from the spatial variation in entry jobs for physicians, which is also typical of medical training positions in other developed countries such as the U.S. (Brotherton & Etzel 2018). Even more, it could apply more generally to the study of the effects of early career experiences on later-life outcomes, as it could naturally arise in per-

[10] We characterize specialties as being less female-represented if their share of females is below the overall proportion in the population of specialized physicians, and we characterize specialties as being more female-represented if their share of females is above the overall proportion. Appendix Table C.2 lists the specialties included in each category.

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

vasive settings where entry jobs are geographically spread out. We therefore turn to investigate the effect of the lottery on households' choice of geographic location in the longer run. One main characterization of geographic locations, which is most relevant to initial placements in our analyzed market of Danish physicians, is the distinction between urban areas and rural areas.[12] We hence begin by studying the effects on residing in rural areas, and we then investigate the associated economic implications for physicians.

Figure 5 plots the propensity to locate in a rural municipality. Consistent with the effects of the lottery on internship relocations (as we have seen in Section 4), the figure shows that both male and female unlucky physicians are much more likely to live in a rural municipality in the short run of the internship period. However, while men and women are both affected by the experimental treatment itself, the longer run paints a different picture. For men, the difference between the lucky and the unlucky largely vanishes within a few years with no detectable effects in the long run. But, for women, we find a persistent significant difference throughout the analysis period. By the tenth year after graduation, households of unlucky females are 4.2 pp more likely to reside in rural areas as compared to the control group. On a counterfactual baseline of 7.3 pp, this represent an increased propensity of over 57%.

We next assess the economic implications of this gender-biased effect. A first consideration follows a simple revealed-preference argument that rural areas are economically unfavorable: since in our setting the control group's choice set is unconstrained, their choices indicate that rural locations are suboptimal from the physicians' perspective.[13]

Moreover, we directly investigate the quasi-experiment's economic implications for physicians' opportunities in terms of the local labor market they operate in. Panel A of Figure 6 studies the effect of the lottery on the local labor market's overall concentration of peer physicians. We construct this measure as the log of the number of physicians in one's range of experience relative to the size of the local population.[14] In line with the results above, both males and females are affected in the short run of the internship, but only unlucky females display persistent effects. This result is of interest for two reasons. First, it suggests that unlucky

[12]We define rural municipalities based on Danish government definitions that use population size and traveling distance to a city center.

[13]To also capture a sense of "amenities," we use the population registers to characterize the economic outcomes of local residents. Panel B of Appendix Table C.1 shows that compared to urban areas, rural areas are characterized by lower wealth, lower annual incomes, a greater reliance on government transfers, and a smaller share of college graduates. A recent report by the Danish Economic Council (DØRS 2015) also describes how rural areas have less access to public sector amenities such as educational institutions and hospitals.

[14]Specifically, we count the number of physicians that are at most one year apart from a physician's year of graduation and we normalize it by the number of local residents.

females are more likely to locate in areas that are less preferred by their peers, corroborating the revealed preference logic. Second, as this measure captures the degree of potential peer competition, it 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.[15]

Another measure that speaks directly to local labor markets' career opportunities for physicians is their attachment to university teaching hospitals. Teaching hospitals, which are located in the vicinity of university cities, are the institutions where skill-intensive procedures are performed, state of the art technologies are first adopted, and innovative medical research is conducted. Association with these hospitals is hence considered advantageous in physicians' resumes, in terms of both high-quality advanced training and competitive career positions. Accordingly, panel B of Figure 6 studies graduating physicians' probability of holding a position at a university hospital in a given year. We again find that males and females are similarly affected in the shorter run, as the entry jobs available for the unlucky essentially block their access to teaching hospitals. However, only females have lingering adverse effects in the longer run, where males manage to converge to the control group's pattern. By the end of our analysis period of ten years, unlucky females' annual propensity to hold a position at a university hospital in 8.9 pp lower; a meaningful negative effect of 17% (on a counterfactual of 52.4 pp).

To conclude, it may be useful to provide as a benchmark the association between location and future economic positions of physicians. In panel A of Appendix Table C.1 we show how, in the longer run, physicians' residential location in rural areas is associated with meaningfully lower wealth and annual incomes.

7 Potential Mechanisms and Mediating Factors

We have found significant gender gaps in the effect of early career experiences on life-cycle outcomes. In this section, we investigate potential mechanisms that could explain or affect our two main results of the adverse longer run effects on women; that is, their lower rate of human capital investment and higher propensity to reside in disadvantaged rural areas. First, we investigate the importance of skills. Second, we investigate family formation. Third, we investigate the protective role of the family and risk sharing within the household.

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

Skills. We begin by studying the importance of skills in potentially mitigating the adverse effect of poor early career circumstances. We proxy for skills using high-school GPA, and we split our sample by whether individuals have a GPA that is above or below the median.[16] Columns 2-3 of Table 1 provide the corresponding estimates of specification (2) for each gender separately, for the probability of being on a research track and the propensity to reside in a rural municipality.

Overall, we find that the adverse effects of a low lottery rank on females are primarily driven by the low-skilled women. They exhibit a 8.5 pp decline in the probability of obtaining a PhD and being on a research track ten years after graduation. As for males, there are no detectable effects in the longer run for high-skilled females. Interestingly, we see the same pattern for living in a rural municipality. Similar to males who experience only short run disruptions during the internship duration, unlucky high-skilled females have no detectable effects in the later periods as they transition to their longer run labor market positions. But unlucky low-skilled female physicians have persistent effects that amount to a 5.7 pp higher probability of living in a rural municipality toward the end of our analysis horizon. Together, this suggests that skills could serve as a protective factor in mitigating the adverse effects on women of poor early circumstances in the labor market.

Family Formation. Graduation from medical school occurs on average around age 28.5, which could represent formative years with respect to family formation. Hence, it times and potentially intertwines labor market and career decisions with family formation outcomes and choices. This captures the common natural interplay between labor market and marriage market choices at the early stages in individuals' working lives. The literature has highlighted how family responsibilities could hinder females' advancement in the labor market, and we are therefore interested in analyzing whether effects on family formation could potentially explain the adverse labor market outcomes of unlucky women.

In Figure 7 we investigate two family formation outcomes: the probability of having a partner, and the number of children in a household. We find no effects for either males or females on either outcome, so that the effects are not likely mediated by family obligations in our case. That is, in our context, the evidence does not seem to support the notion that unlucky women may crowd out career considerations by, for example, being more oriented toward family consider-

[16] It is worth noting that all physicians have GPAs that are high in the distribution of high-school GPA, as there is a high GPA cutoff for entering medical schools.

ations when they experience adverse labor market conditions at the beginning of their working life.

Protective Role of the Family and Household Risk Sharing. Next, we investigate the potential protective role of the family. One of the key potential gains from marriage, as highlighted in the family economics literature, is risk sharing and self-insurance within the family (see, e.g., Browning et al. 2013). That is, as individuals face idiosyncratic income risk, they have an obvious incentive to mutually provide insurance. Within the family, risk sharing involves intra-household actions and transfers that alleviate the impact of shocks affecting one spouse. Hence, under the assumption of risk sharing, we would expect unlucky married individuals to experience effects to a lesser extent compared to unlucky single individuals. We note that such potential mitigation is not obvious ex-ante. When commitment is challenged, bad realizations to one spouse could lead to re-negotiations that could alternatively result in married unlucky individuals being in a worse position.

We therefore turn to empirically study the effects of the quasi-experiment by marital status at the time the shock is realized. Specifically, we split the sample by whether the graduating physician was single or had a registered partner in the year prior to the lottery. Columns 4-5 of Table 1 provide estimates by this sample split for our main outcomes by gender. The evidence points to unlucky single women as driving the adverse long run results for females. Whereas there is no detectable effect for unlucky married women at the end of the analysis horizon, unlucky women who experienced the shocks as singles are 7.3 pp less likely to be on a research career track in the longer run. We reach similar conclusions for the longer run effects on the geography of residence, where only unlucky single females exhibit a 5.8 pp higher probability of living in a rural municipality. There are no detectable effects in the long run among males. We view these results as evidence in support of risk sharing and self-insurance within the family. Specifically, they suggest a protective role of the household that can mitigate idiosyncratic labor market risks, here in the context of important effects of early working life experiences.

Finally, one way in which intra-household actions of risk sharing could be manifested is changes to the spouse's career trajectories. For example, to accommodate the shock to one spouse, the other spouse may be induced to temporary put on hold their own professional plans. Within our data, we can test for delays in spousal career advancement in the following way: among graduating physicians in pre-existing couples, does the lottery affect the probability or timing of the other spouse completing their medical education? Statistically, such analysis is meaningful as more than 12 percent of households of graduating physicians are comprised of two physicians in the longer run (as manifested by the control group's trajectory in the figures that follow). Interestingly, Figure 8 reveals differential family spillovers by gender. Whereas husbands of graduating wives are unaffected, wives of unlucky graduating males are induced to temporarily postpone their timing of becoming a doctor, affecting their own career advancement. This points to an additional gender asymmetry in the effects of early career experiences on households: women unevenly bear the burden of early life experiences, even in the context of spillovers within the household.

8 Conclusion

In this paper we show how early career experiences causally determine long run labor market and life-cycle outcomes differentially for males and females. Females who face adverse labor market shocks early in their careers experience persistent negative effects on their long run labor market outcomes, which in turn translate into lower life-cycle income trajectories. Males do not exhibit such effects and manage to overcome any transitory adverse effects in the long run. We therefore offer and provide evidence of a novel key route by which gender gaps in economic outcomes can initiate and perpetuate.

We also provide analysis that sheds light on what can and cannot explain the results among several leading potential channels. The findings do not support the hypothesis of differential family responsibilities, and they suggest a protective role of ability. We additionally find that the family can act as an important self-insurance mechanism against labor market shocks as the effect on married women is meaningfully attenuated. Lastly, we wish to highlight that as the gender-neutral quasi-experiment induced similar treatments across males and females, the gender-biased results point to diverging paths and differential effects of similar economic shocks. Moreover, due to the nature of our setting—where control households could make choices similar to treatment households but choose not to—the findings are unlikely to reflect internal gender differences in preferences. Rather, they likely reflect external gender gaps in "budget sets" of later-life economic constraints and possibilities. In turn, the analysis suggests that even in environments where males and females face equal early-stage opportunities, important gender gaps can perpetuate in the longer run. Accordingly, policies that aim for gender outcome-based equality may be insufficient if targeted merely at equalizing the starting playing field.

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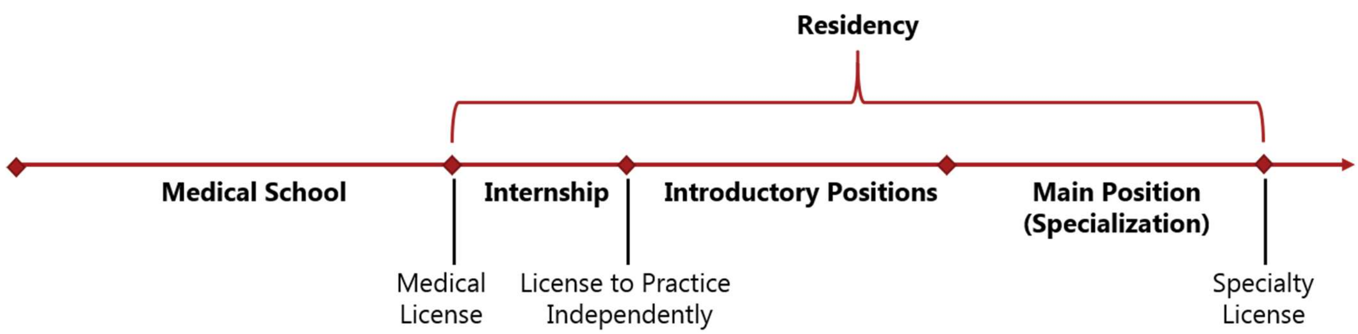
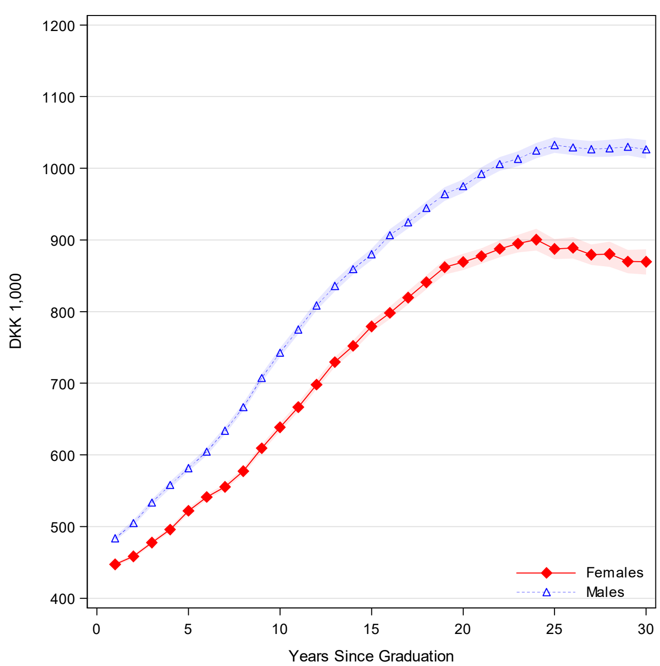
Figure 1: Physicians in Denmark

Panel A: Physician Training



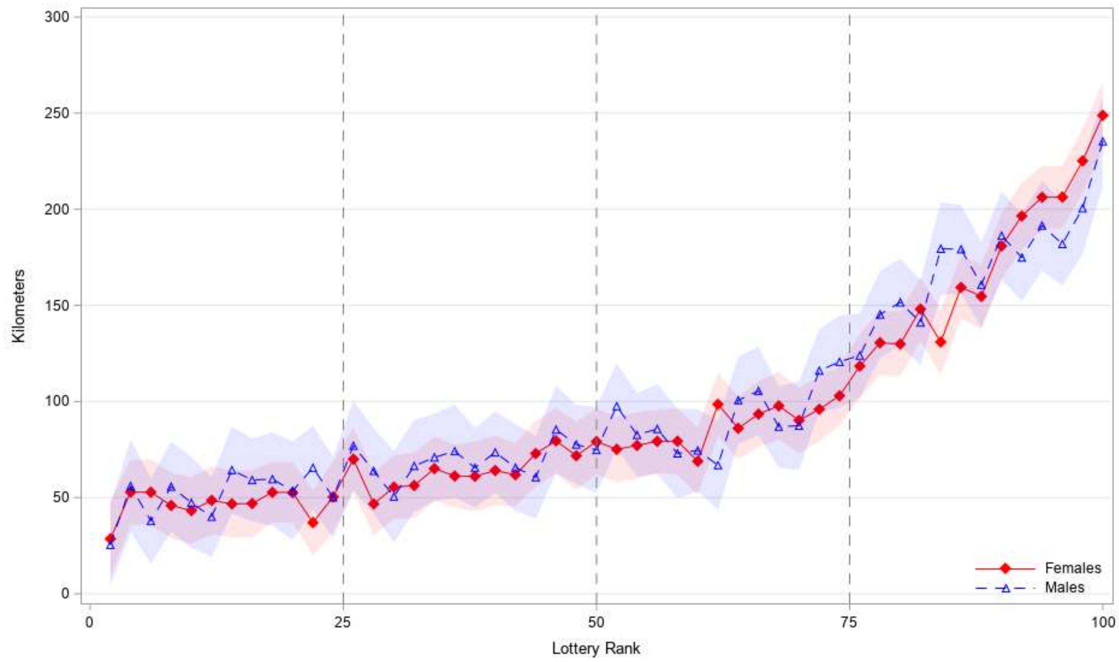
Panel B: Life-Cycle Income Trajectories for Male and Female Physicians



Notes: Panel A plots the process of physician training, from the start of medical school to the acquisition of an independent medical license. Panel B plots the income paths of male and female physicians by years since graduation. 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.

Figure 2: Placement to Internship

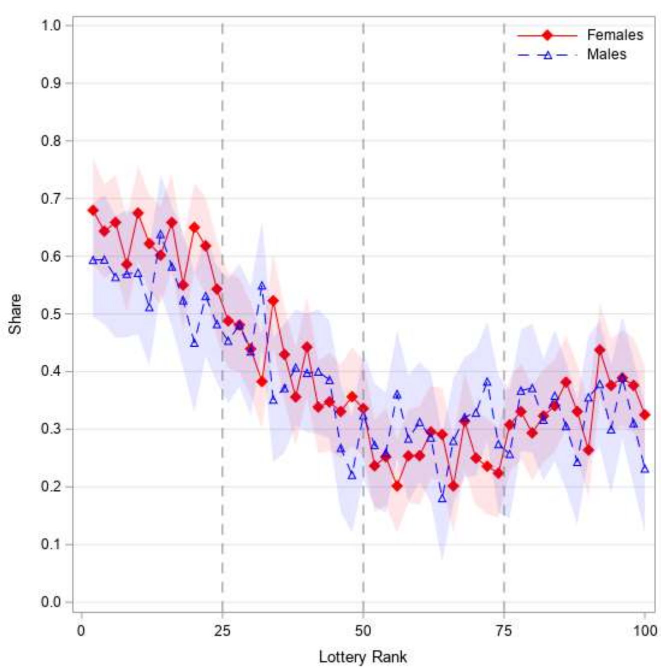
Panel A: Geographic Distance



Panel B: Internship Specialties

B.1: Initial Position

Internal Medicine



Surgery

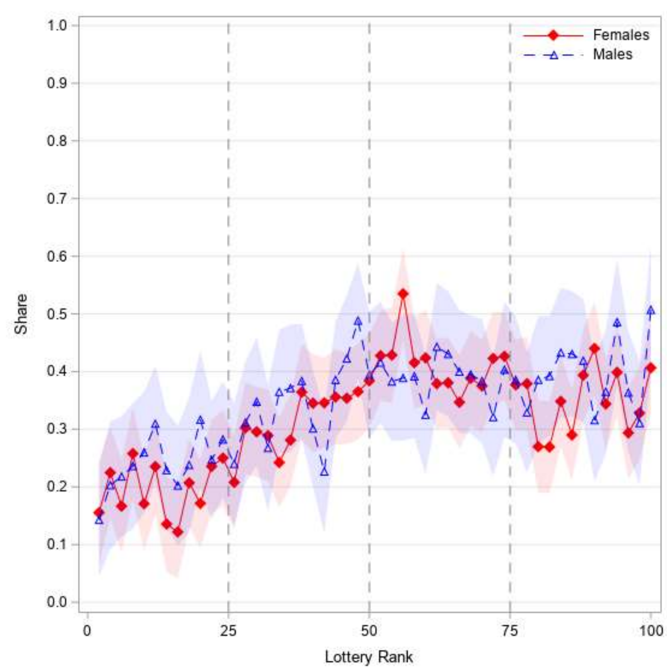
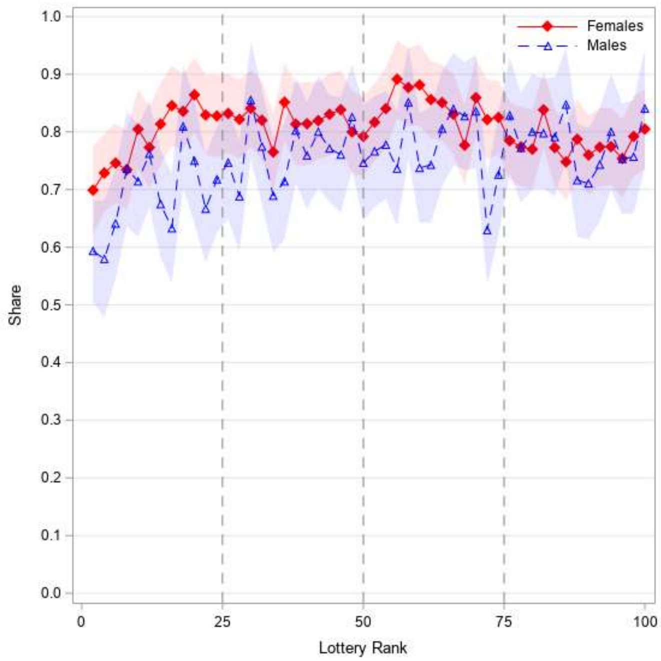


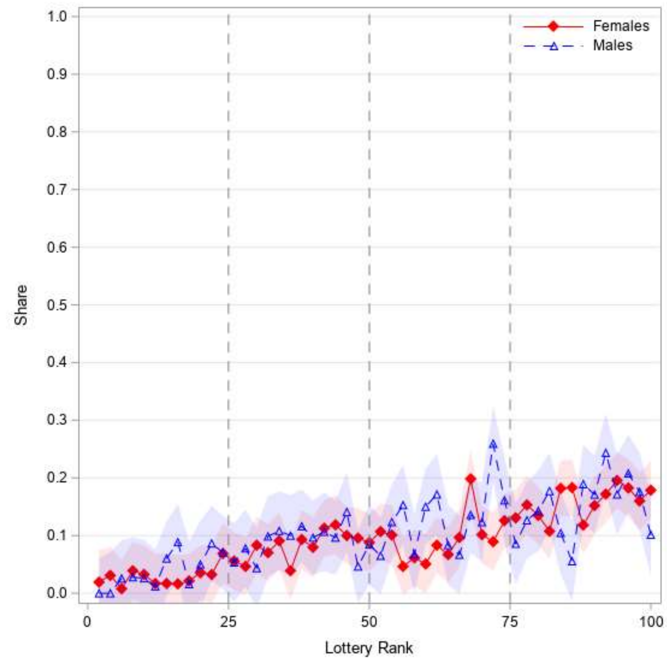
Figure 2: Placement to Internship—*Continued*

B.2: Secondary Position

General Medicine



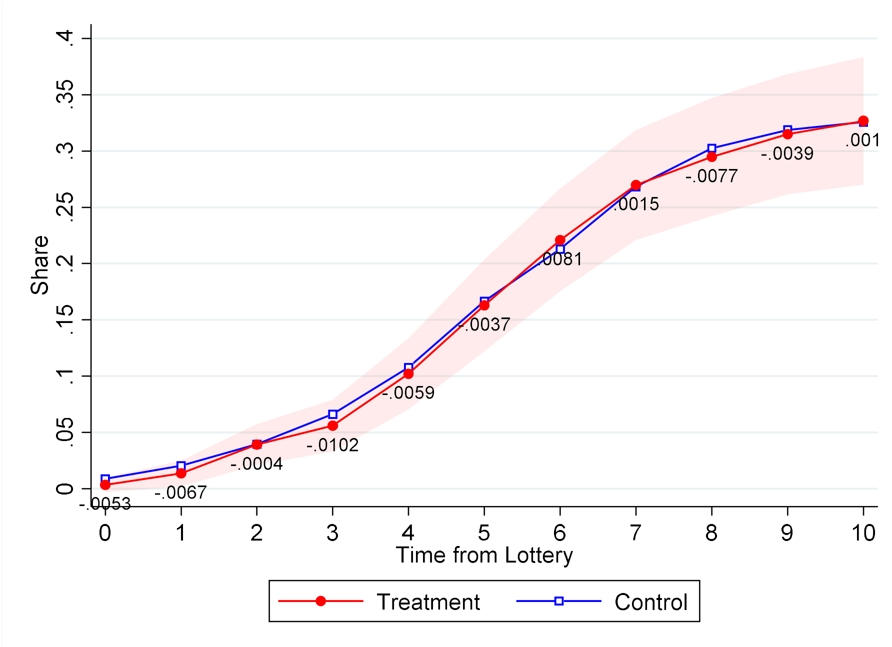
Psychiatry



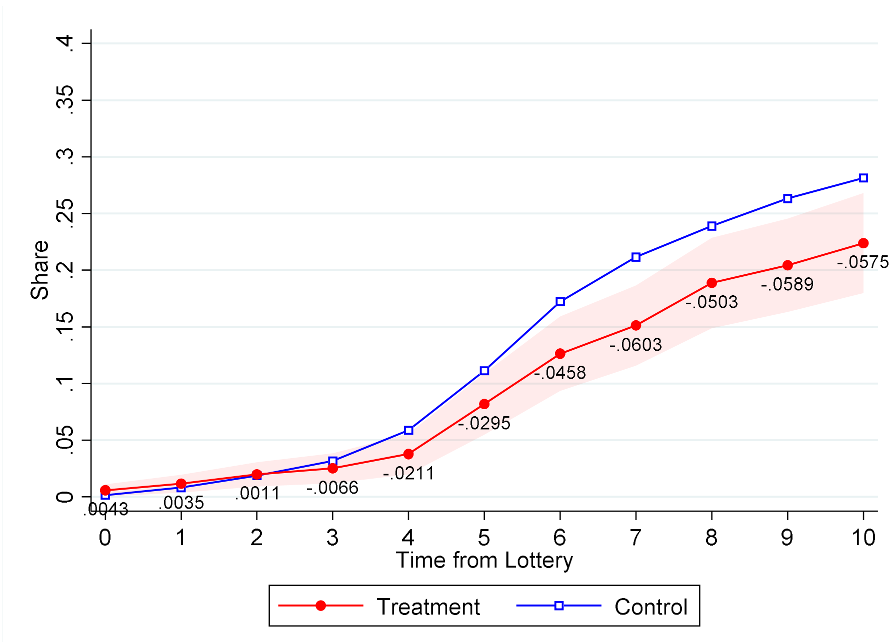
Notes: Panel A plots the distance between a graduating student's pre-internship residential address and the location of the internship placement by lottery rank. We measure distance as the travel distance from the residential zip code when drawing the lottery number (last semester in medical school) to the zip code of the hospital of the matched position. Panel B plots the relationship between internship specialties and lottery rank. We construct equal bins based on the rank of the individual lottery number within a lottery round of each graduating cohort. Shaded areas represent 95-percent confidence intervals.

Figure 3: Human Capital Investment—Probability of Gaining Medical PhD Education

Males



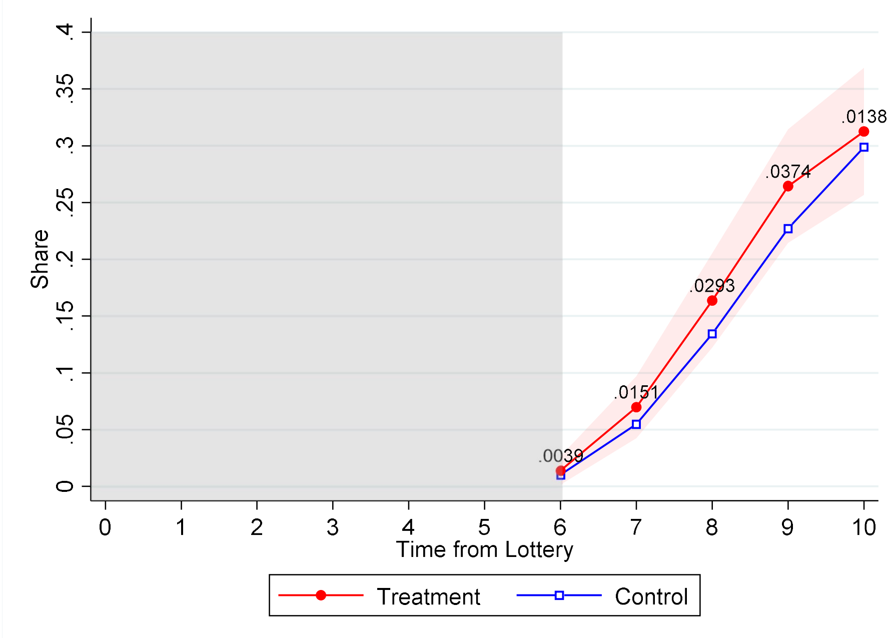
Females



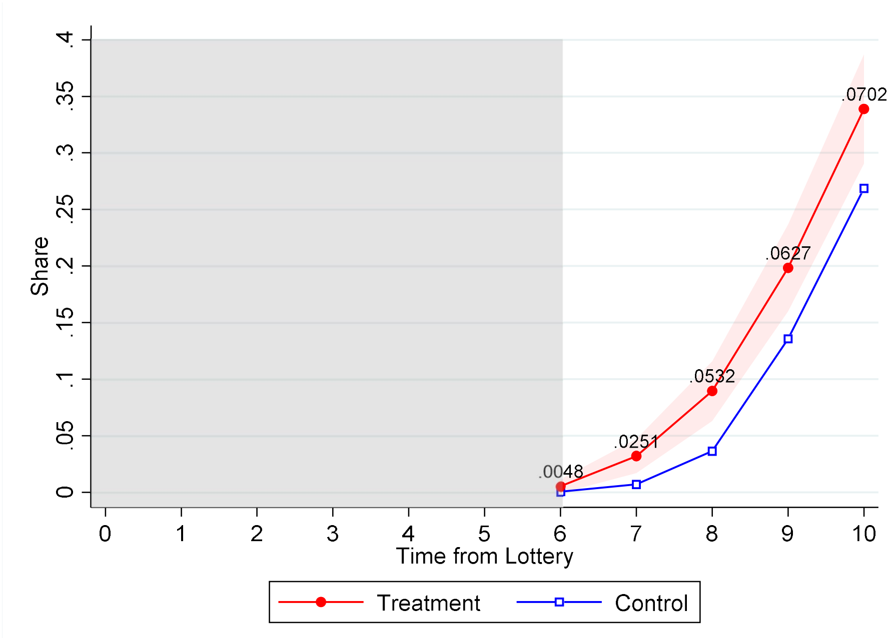
Notes: This figure plots the probability of pursuing a PhD by gender. The blue line and squares represent the counterfactual trajectory by plotting the mean outcomes for the control group of lucky physicians. The red line and circles represent the treatment effects. Specifically, we display the β_τ coefficients from equation (1), along with their 95-percent confidence intervals, by adding them up with the counterfactual levels to capture both levels and treatment effects. The point estimates for β_τ, which equal the vertical distance between the two lines, are reported in black.

Figure 4: Sorting into Female-Represented Medical Specialties

Males



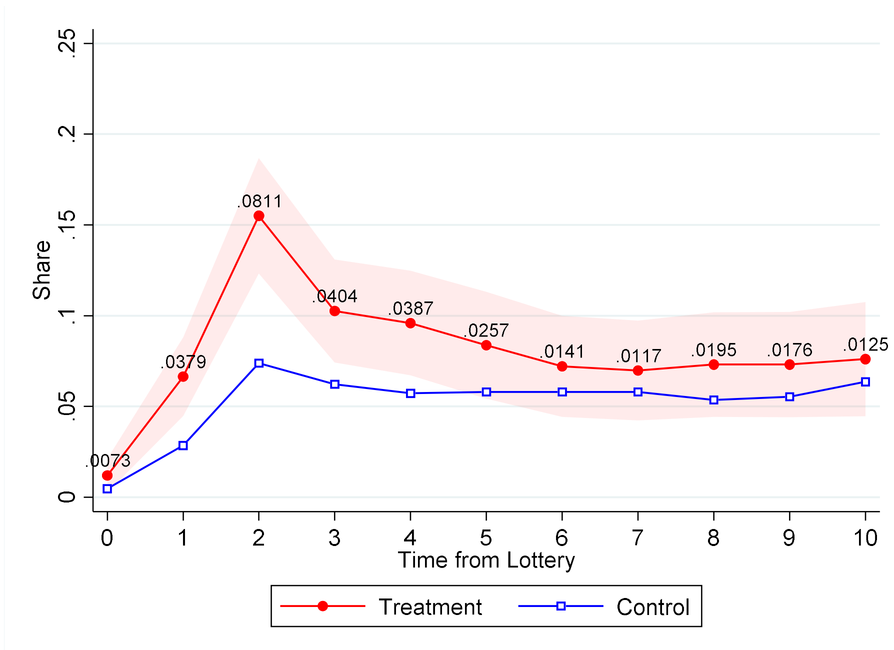
Females



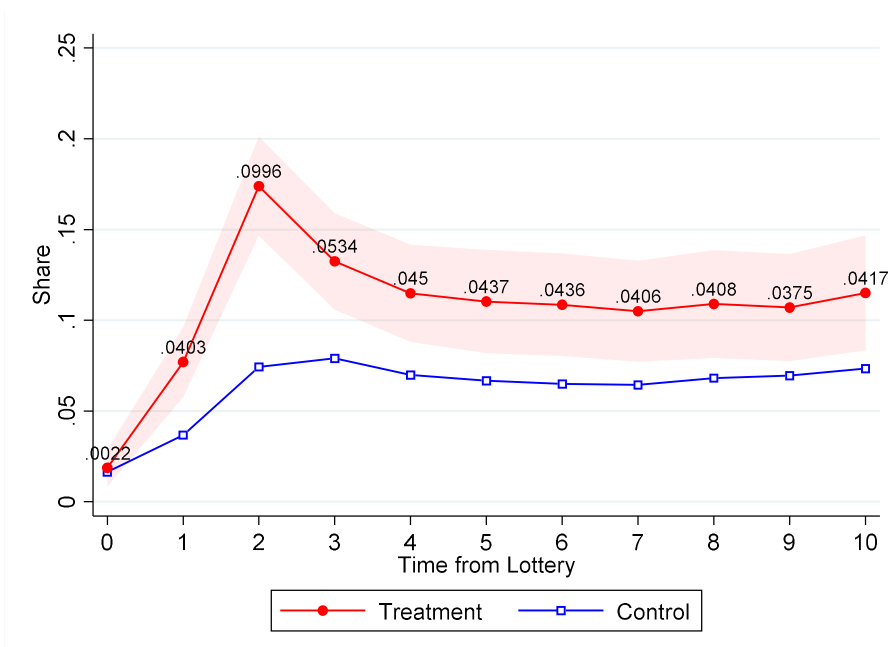
Notes: This figure plots the probability of completing residency in female-represented specialties by gender. The plot starts at year 6 since specialty completion can only occur after a period of 5 years following graduation from medical school. The blue line and squares represent the counterfactual trajectory by plotting the mean outcomes for the control group of lucky physicians. The red line and circles represent the treatment effects. Specifically, we display the β_τ coefficients from equation (1), along with their 95-percent confidence intervals, by adding them up with the counterfactual levels to capture both levels and treatment effects. The point estimates for β_τ, which equal the vertical distance between the two lines, are reported in black.

Figure 5: Household Geographic Location—Residing in Rural Areas

Males



Females

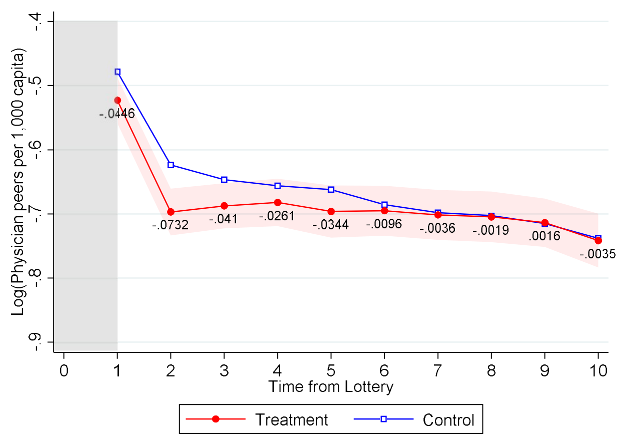


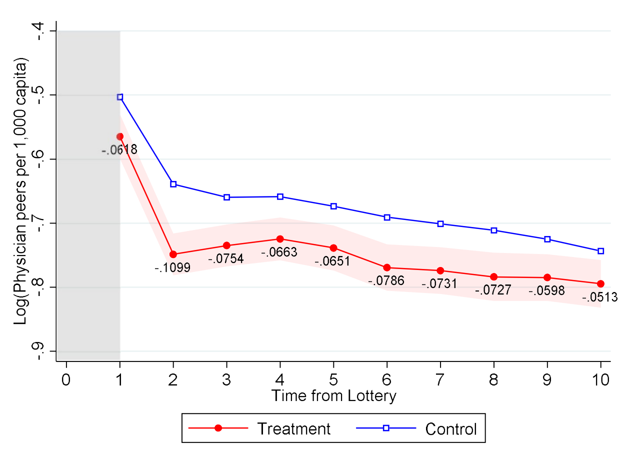
Notes: This figure plots the probability of residing in a rural area by gender. The blue line and squares represent the counterfactual trajectory by plotting the mean outcomes for the control group of lucky physicians. The red line and circles represent the treatment effects. Specifically, we display the β_τ coefficients from equation (1), along with their 95-percent confidence intervals, by adding them up with the counterfactual levels to capture both levels and treatment effects. The point estimates for β_τ, which equal the vertical distance between the two lines, are reported in black.

Figure 6: Local Labor Markets

Panel A: Concentration of Peer Physicians

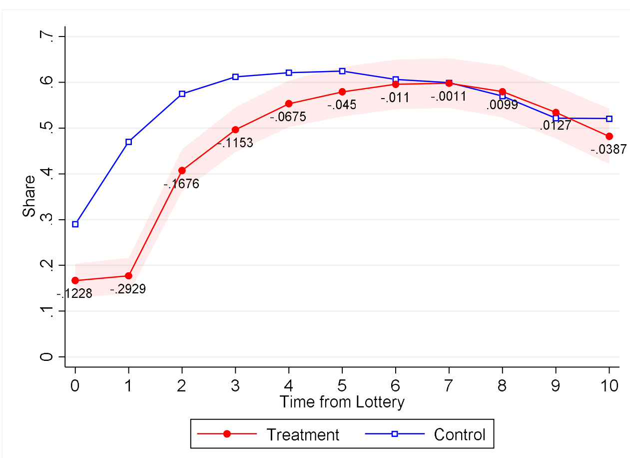
Males | *Females*

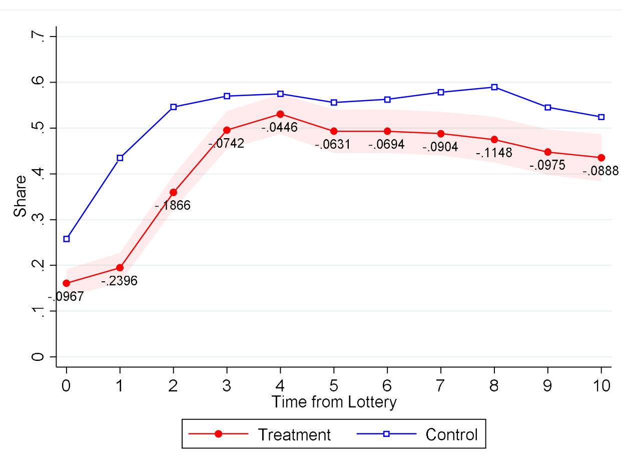




Panel B: Attachment to University Hospitals

Males | *Females*



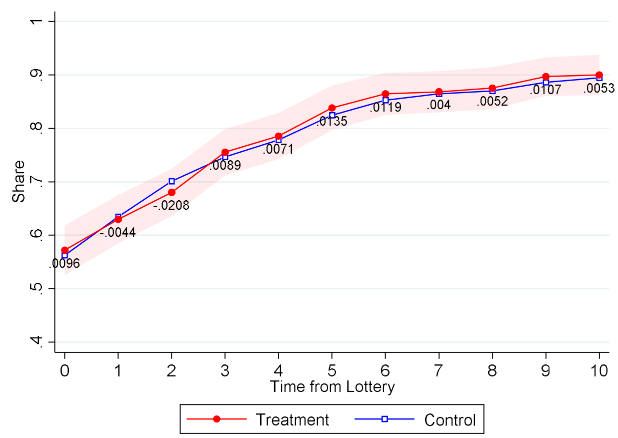


Notes: These figures plot outcomes related to the local labor market that graduating physicians operate in by gender. Panel A plots the concentration of peer physicians. Specifically, we take the log of the number of physicians that are at most one year apart from a physician's year of graduation within a labor market (that includes municipalities within a 50-kilometer radius of a given location) which we normalize by the size of the local population. By construction, this measure begins in period 1. Panel B plots the graduating physicians' probability of holding a position at a university hospital in a given year. The blue line and squares represent the counterfactual trajectory by plotting the mean outcomes for the control group of lucky physicians. The red line and circles represent the treatment effects. Specifically, we display the β_τ coefficients from equation (1), along with their 95-percent confidence intervals, by adding them up with the counterfactual levels to capture both levels and treatment effects. The point estimates for β_τ, which equal the vertical distance between the two lines, are reported in black.

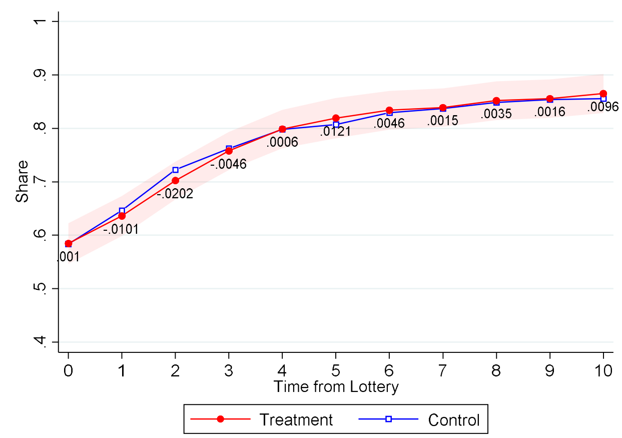
Figure 7: Family Formation

Panel A: Probability of Having a Partner

Males

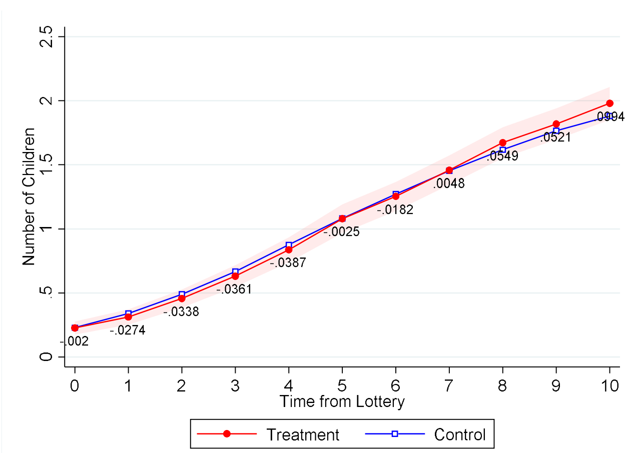


Females

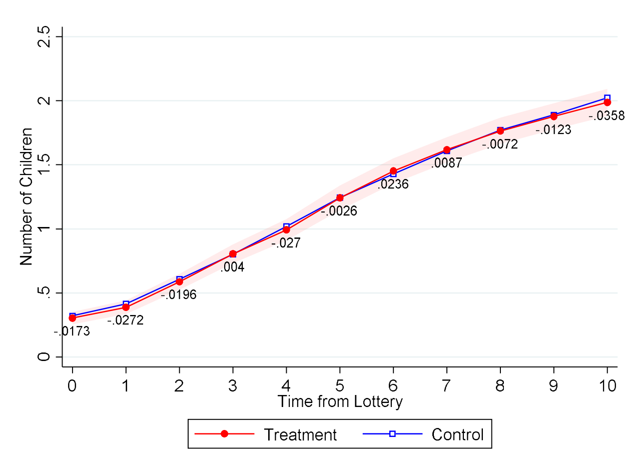


Panel B: Number of Children

Males



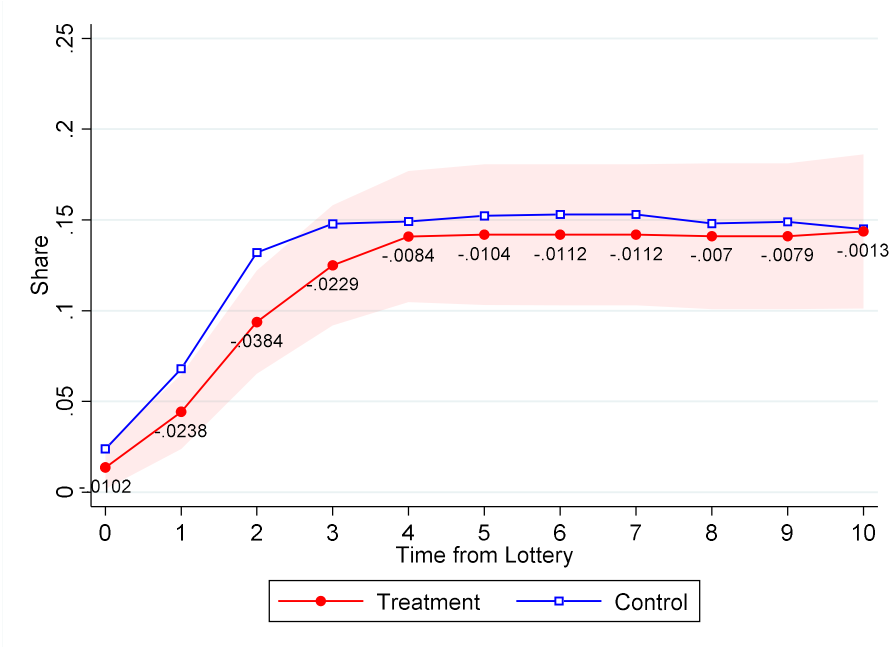
Females



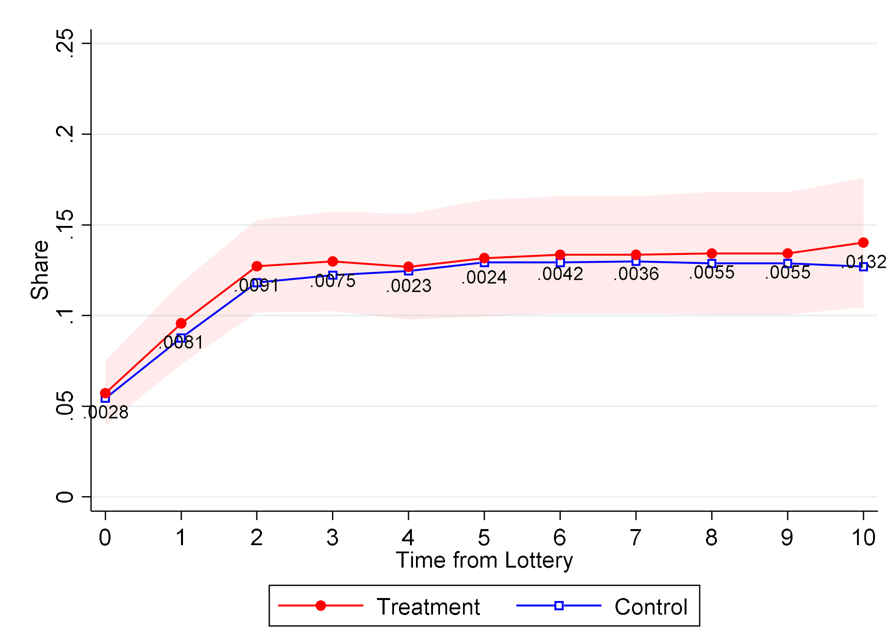
Notes: These figures plot outcomes of family formation by the gender of the graduating physician. The blue line and squares represent the counterfactual trajectory by plotting the mean outcomes for the control group of lucky physicians. The red line and circles represent the treatment effects. Specifically, we display the β_τ coefficients from equation (1), along with their 95-percent confidence intervals, by adding them up with the counterfactual levels to capture both levels and treatment effects. The point estimates for β_τ, which equal the vertical distance between the two lines, are reported in black.

Figure 8: Family Spillovers—Dynamics of Spousal Human Capital Accumulation

Males



Females



Notes: This figure plots the rate of completion of medical schools by the graduating physicians' spouses, split by the gender of the graduating physicians. The outcome variable is an indicator that assumes the value 1 if a graduating physician' spouse (as matched at the baseline period -1) has graduated medical school at a given period, and it assumes the value 0 otherwise. The blue line and squares represent the counterfactual trajectory by plotting the mean outcomes for the control group of lucky physicians. The red line and circles represent the treatment effects. Specifically, we display the β_τ coefficients from equation (1), along with their 95-percent confidence intervals, by adding them up with the counterfactual levels to capture both levels and treatment effects. The point estimates for β_τ, which equal the vertical distance between the two lines, are reported in black.

Table 1: The Effects of Early Career Experiences by Gender—Heterogeneity

Panel A: Males

Obtaining a PhD

	(1) All	(2) Lower GPA	(3) Higher GPA	(4) Single	(5) Partnered
Treat	-0.0024	-0.0227	0.0092	0.0117	-0.0182
	(0.0254)	(0.0327)	(0.0385)	(0.0360)	(0.0357)
Constant	0.3026***	0.2604***	0.3538***	0.3120***	0.2925***
	(0.0131)	(0.0170)	(0.0203)	(0.0184)	(0.0188)
Observations	5,977	3,199	2,778	3,110	2,867
Clusters	1,619	866	753	841	778

Residing in Rural Areas

	(1) All	(2) Lower GPA	(3) Higher GPA	(4) Single	(5) Partnered
Treat	0.0153	0.0308	-0.0004	0.0218	0.0084
	(0.0141)	(0.0209)	(0.0189)	(0.0180)	(0.0219)
Constant	0.0575***	0.0565***	0.0588***	0.0434***	0.0728***
	(0.0066)	(0.0089)	(0.0099)	(0.0078)	(0.0108)
Observations	5,977	3,199	2,778	3,110	2,867
Clusters	1,619	866	753	841	778

Panel B: Females

Obtaining a PhD

	(1) Main	(2) Lower GPA	(3) Higher GPA	(4) Single	(5) Partnered
Treat	-0.0566***	-0.0849***	-0.0296	-0.0727***	-0.0410
	(0.0188)	(0.0227)	(0.0303)	(0.0263)	(0.0270)
Constant	0.2471***	0.2141***	0.2877***	0.2462***	0.2479***
	(0.0101)	(0.0129)	(0.0159)	(0.0145)	(0.0141)
Observations	8,349	4,550	3,799	4,007	4,342
Clusters	2,287	1,256	1,031	1,104	1,183

Residing in Rural Areas

	(1) Main	(2) Lower GPA	(3) Higher GPA	(4) Single	(5) Partnered
Treat	0.0402***	0.0568***	0.0219	0.0579***	0.0236
	(0.0145)	(0.0210)	(0.0198)	(0.0209)	(0.0201)
Constant	0.0686***	0.0687***	0.0686***	0.0595***	0.0769***
	(0.0061)	(0.0082)	(0.0090)	(0.0080)	(0.0090)
Observations	8,349	4,550	3,799	4,007	4,342
Clusters	2,287	1,256	1,031	1,104	1,183

Notes: This table reports estimates of the effects of the lottery by various sample splits for each gender separately, based on specification (2). Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix

Appendix A: Sample Characteristics

Appendix Table A.1: Summary Statistics

Panel A: All

	Mean		Difference	Test Stat.	*P*-value
	Control	Treatment			
	(1)	(2)	(3)	(4)	(5)
Female	0.5980	0.5935	0.0045	0.3013	0.7632
			(0.0149)		
Age	28.5449	28.4986	0.0463	0.6416	0.5212
			(0.0721)		
Partnered	0.5040	0.4979	0.0061	0.3978	0.6908
			(0.0152)		
Joint Lottery	0.1155	0.1039	0.0117	1.2110	0.2259
			(0.0096)		
Number of Children	0.2837	0.2722	0.0115	0.6330	0.5268
			(0.0182)		
GPA	9.6092	9.6320	-0.0228	0.6330	0.5268
			(0.0182)		
Total Observations	5,720				

Panel B: Males

	Mean		Difference	Test Stat.	*P*-value
	Control	Treatment			Control
	(1)	(2)	(3)	(4)	(5)
Age	28.6172	28.4685	0.1487	1.3054	0.1919
			(0.1139)		
Partnered	0.4799	0.4685	0.0114	-0.4794	0.6317
			(0.0239)		
Joint Lottery	0.1350	0.1278	0.0072	0.4430	0.6578
			(0.0162)		
Number of Children	0.2286	0.2266	0.0020	0.0796	0.9366
			(0.0257)		
GPA	9.5773	9.6121	-0.0348	-0.4521	0.6512
			(0.0769)		
Total Observations	2,306				

Appendix Table A.1: Summary Statistics—*Continued*

Panel C: *Females*

	Mean		Difference	Test Stat.	*P*-value
	Control	Treatment			Control
	(2)	(3)	(4)	(5)	(6)
Age	28.4963	28.5193	-0.0230	-0.2464	0.8054
			(0.0932)		
Partnered	0.5201	0.5181	0.0021	-0.1042	0.9170
			(0.0197)		
Joint Lottery	0.1025	0.0875	0.0149	1.2698	0.2042
			(0.0118)		
Number of Children	0.3207	0.3034	0.0173	0.6928	0.4885
			(0.0250)		
GPA	9.6307	9.6456	-0.0149	-0.2549	0.7988
			(0.0586)		
Total Observations	3,414				

Notes: These tables provide summary statistics for the analysis samples 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. Individuals' characteristics include gender, age, indicators for whether the physician had a registered partner and whether they applied for the lottery jointly, number of children, and high-school GPA. Column 1 displays means for our control group of individuals in the first three lottery rank quartiles (most lucky), and column 2 displays means for our treatment group of individuals in the highest quartile (most unlucky). Column 3 provides the differences between column 1 and column 2, along with their standard errors. Column 4 reports the *t*-statistics for continuous variables and *z*-statistics for the binary variables. Column 5 reports the *p*-values of the test statistics.

Appendix B: Empirical Design—Validation and Robustness

Appendix Table B.1: Design Validation

Panel A: Lottery Rank

	Lottery Rank (1-100)	
	(1)	(2)
Gender	0.2150	0.2268
	(0.7845)	(0.7875)
Age	-0.0354	-0.0487
	(0.1862)	(0.1891)
Partnered	0.7357	0.7373
	(0.8322)	(0.8353)
Joint Lottery	-0.8258	-0.7907
	(1.2184)	(1.2346)
Number of Children	-0.0816	-0.0676
	(0.7569)	(0.7603)
GPA	0.1544	0.1620
	(0.2635)	(0.2680)
Round FE		X
Observations	5,720	5,720
R-Squared	0.0003	0.0006
F-Statistic	0.29	0.14
F Test	0.9421	1.0000

	Lottery Rank by Gender			
	Males	Males	Females	Females
	(1)	(2)	(3)	(4)
Age	-0.2952	-0.2397	0.1687	0.0876
	(0.2826)	(0.2867)	(0.2480)	(0.2527)
Partnered	-0.1395	-0.2132	1.4145	1.3623
	(1.3066)	(1.3137)	(1.0832)	(1.0880)
Joint Lottery	0.6728	0.4313	-2.1001	-1.8632
	(1.7910)	(1.8200)	(1.6657)	(1.6898)
Number of Children	0.0844	0.1251	-0.4148	-0.3279
	(1.2710)	(1.2811)	(0.9517)	(0.9577)
GPA	0.2519	0.3649	0.0577	-0.0253
	(0.3949)	(0.4024)	(0.3544)	(0.3608)
Round FE		X		X
Observations	2,306	2,306	3,414	3,414
R-Squared	0.0011	0.0062	0.0011	0.0045
F-Statistic	0.50	0.59	0.75	0.64
F Test	0.7785	0.9399	0.5863	0.9123

Appendix Table B.1: Design Validation—*Continued*

Panel B: Highest Rank Quartile

	Highest Rank Quartile (1)	(2)
Gender	-0.0041	-0.0039
	(0.0118)	(0.0118)
Age	-0.0011	-0.0011
	(0.0028)	(0.0028)
Partnered	-0.0009	-0.0008
	(0.0125)	(0.0125)
Joint Lottery	-0.0230	-0.0235
	(0.0183)	(0.0185)
Number of Children	-0.0038	-0.0037
	(0.0114)	(0.0114)
GPA	0.0011	0.0013
	(0.0040)	(0.0040)
Round FE		X
Observations	5,720	5,720
R-Squared	0.0004	0.0008
F-Statistic	0.39	0.18
F Test	0.8845	1.0000

	Highest Rank Quartile by Gender			
	Males	Males	Females	Females
	(1)	(2)	(3)	(4)
Age	-0.0056	-0.0048	0.0024	0.0015
	(0.0043)	(0.0043)	(0.0037)	(0.0038)
Partnered	-0.0078	-0.0092	0.0049	0.0043
	(0.0197)	(0.0198)	(0.0162)	(0.0163)
Joint Lottery	-0.0129	-0.0194	-0.0316	-0.0271
	(0.0270)	(0.0274)	(0.0250)	(0.0254)
Number of Children	0.0098	0.0098	-0.0137	-0.0128
	(0.0191)	(0.0193)	(0.0143)	(0.0144)
GPA	0.0001	0.0025	0.0018	0.0004
	(0.0059)	(0.0061)	(0.0053)	(0.0054)
Round FE		X		X
Observations	2,306	2,306	3,414	3,414
R-Squared	0.0010	0.0055	0.0008	0.0029
F-Statistic	0.46	0.52	0.53	0.42
F Test	0.8060	0.9721	0.7514	0.9946

Notes: This table tests the validity of the lottery in terms of random assignment. Panel A runs regressions of the lottery rank (from 1-100) on physicians' baseline characteristics. These characteristics include gender, age, indicators for whether the physician had a registered partner and whether they applied for the lottery jointly, number of children, and high-school GPA. We run the corresponding specifications for each gender separately as well. Panel B runs similar regressions but where the outcome variable is an indicator for drawing a lottery number at the highest rank quartile (most unlucky). 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 Table B.2: Alternative Definitions of Treatment and Control Groups

Panel A: *Males*

Obtaining a PhD

	Percentile						
	17	*20*	*23*	*25*	*27*	*30*	*33*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat	0.0032	0.0008	0.0079	-0.0024	-0.0162	0.0001	0.0159
	(0.0294)	(0.0276)	(0.0264)	(0.0254)	(0.0246)	(0.0240)	(0.0238)
Constant	0.3014***	0.3018***	0.3001***	0.3026***	0.3066***	0.3020***	0.2966***
	(0.0124)	(0.0127)	(0.0129)	(0.0131)	(0.0134)	(0.0137)	(0.0138)
Observations	5,977	5,977	5,977	5,977	5,977	5,977	5,977
Clusters	1,619	1,619	1,619	1,619	1,619	1,619	1,619

Residing in Rural Areas

	Percentile						
	17	*20*	*23*	*25*	*27*	*30*	*33*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat	0.0026	0.0095	0.0090	0.0153	0.0171	0.0112	0.0148
	(0.0155)	(0.0150)	(0.0143)	(0.0141)	(0.0137)	(0.0130)	(0.0128)
Constant	0.0611***	0.0596***	0.0594***	0.0575***	0.0567***	0.0580***	0.0565***
	(0.0064)	(0.0065)	(0.0066)	(0.0066)	(0.0067)	(0.0069)	(0.0069)
Observations	5,977	5,977	5,977	5,977	5,977	5,977	5,977
Clusters	1,619	1,619	1,619	1,619	1,619	1,619	1,619

Panel A: *Females*

Obtaining a PhD

	Percentile						
	17	*20*	*23*	*25*	*27*	*30*	*33*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat	-0.0536**	-0.0580***	-0.0559***	-0.0566***	-0.0428**	-0.0460**	-0.0406**
	(0.0216)	(0.0202)	(0.0192)	(0.0188)	(0.0187)	(0.0181)	(0.0177)
Constant	0.2421***	0.2446***	0.2460***	0.2471***	0.2445***	0.2467***	0.2465***
	(0.0095)	(0.0097)	(0.0100)	(0.0101)	(0.0102)	(0.0104)	(0.0107)
Observations	8,349	8,349	8,349	8,349	8,349	8,349	8,349
Clusters	2,287	2,287	2,287	2,287	2,287	2,287	2,287

Residing in Rural Areas

	Percentile						
	17	*20*	*23*	*25*	*27*	*30*	*33*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat	0.0359**	0.0436***	0.0440***	0.0402***	0.0371***	0.0347***	0.0325**
	(0.0169)	(0.0161)	(0.0151)	(0.0145)	(0.0139)	(0.0133)	(0.0127)
Constant	0.0725***	0.0699***	0.0685***	0.0686***	0.0686***	0.0683***	0.0678***
	(0.0059)	(0.0059)	(0.0060)	(0.0061)	(0.0062)	(0.0063)	(0.0064)
Observations	8,349	8,349	8,349	8,349	8,349	8,349	8,349
Clusters	2,287	2,287	2,287	2,287	2,287	2,287	2,287

Notes: These tables investigate the robustness of our design by studying the effects on our main longer run outcomes when we vary the percentiles that define the treatment and control groups. We report estimates of the effects of the lottery for each gender separately, based on specification (2). Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix Table B.3: Linear Specifications

Panel A: Males

Obtaining a PhD

	Highest Quartile (1)	Lottery Rank (2)
Treat	-0.0024	0.0002
	(0.0254)	(0.0004)
Constant	0.3026***	0.2929***
	(0.0131)	(0.0226)
Observations	5,977	5,977
Clusters	1,619	1,619

Residing in Rural Areas

	Highest Quartile (1)	Lottery Rank (2)
Treat	0.0153	0.0003
	(0.0141)	(0.0002)
Constant	0.0575***	0.0486***
	(0.0066)	(0.0112)
Observations	5,977	5,977
Clusters	1,619	1,619

Panel A: Females

Obtaining a PhD

	Highest Quartile (1)	Lottery Rank (2)
Treat	-0.0566***	-0.0006**
	(0.0188)	(0.0003)
Constant	0.2471***	0.2640***
	(0.0101)	(0.0175)
Observations	8,349	8,349
Clusters	2,287	2,287

Residing in Rural Areas

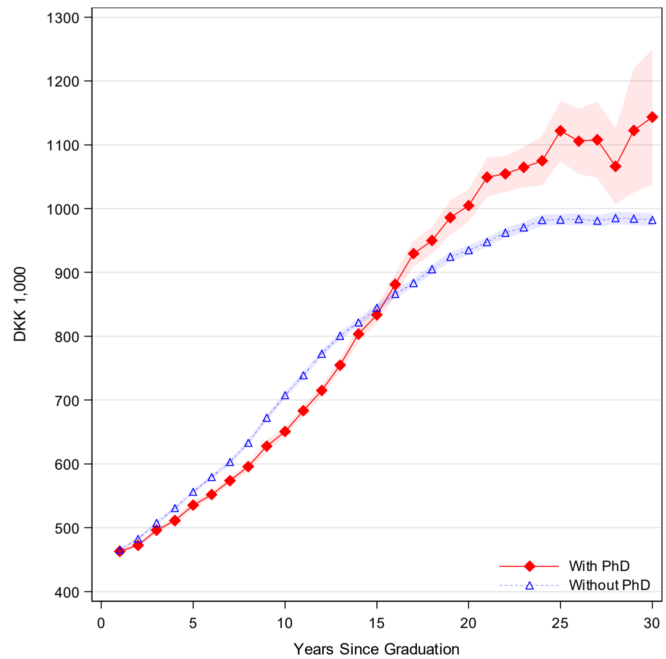
	Highest Quartile (1)	Lottery Rank (2)
Treat	0.0402***	0.0005***
	(0.0145)	(0.0002)
Constant	0.0686***	0.0513***
	(0.0061)	(0.0106)
Observations	8,349	8,349
Clusters	2,287	2,287

Notes: These tables investigate the robustness of our design by studying the effects on our main longer run outcomes when we use a linear specification in lottery rank. Column 2 reports estimates of the effects of the lottery for each gender separately, based on a version of specification (2) where the variable *Treat* is the lottery rank (from 1-100). Robust standard errors clustered at the individual level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

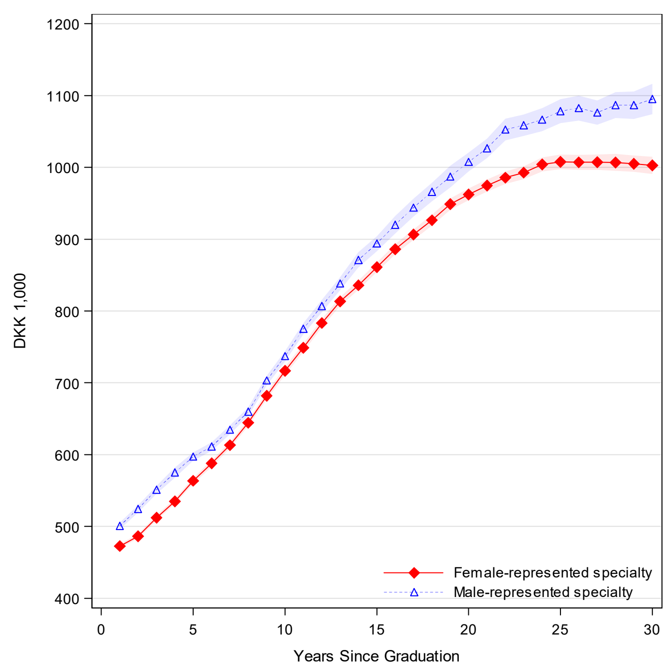
Appendix C: Additional Figures and Tables

Appendix Figure C.1: Life-Cycle Income Trajectories

Panel A: Income with and without a Medical PhD



Panel B: Income by Specialties' Gender Representativeness



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 Table C.1: Characterization of Geographic Locations

Panel A: Long Run Economic Positions of Physicians

	Wealth	Annual Income
	(1)	(2)
Urban	3,398***	932***
	(40)	(6)
Rural Difference	-814***	-56***
	(69)	(10)
Number of Individuals	11,741	15,346

Panel B: Location Based Population Characteristics

	Wealth	Annual Income	College	Government Transfers
	(1)	(2)	(3)	(4)
Urban	1,235***	409***	0.3903***	0.2523***
	(4)	(0.7)	(0.0005)	(0.0003)
Rural Difference	-108***	-53***	-0.0543***	0.02115***
	(6)	(0.8)	(0.0009)	(0.0006)
Number of Individuals	2,491,143	2,491,143	1,528,986	2,166,488

Notes: These tables assess differences in economic outcomes across urban and rural municipalities in Denmark. Panel A assesses the longer run financial positions of physicians. Wealth is measured at the approximated life-cycle peak using observations from years 25-30 after graduation from medical school. Annual income measures income from any source (including pre-tax earnings, capital income, government transfers, and self-employment business revenues) and uses observations from 25 years after graduation. In this regression we use frequency weights based on years since graduation to account for the time structure of the data. Panel B describes the local population's characteristics based on all individuals of ages 45-60 in a given location. Government transfers captures an indicator for whether an individual's transfers are higher than the mean value (of DKK 46,042). Data are taken from years 2000 onward, and monetary are presented in DKK 1,000.

Appendix Table C.2: Specialty Grouping

Specialty	Specialty Group
Panel A: Less Female-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: More 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 female representativeness. We characterize a specialty as less female-represented if its share of females is below the overall proportion in the population of specialized physicians, and we characterize a specialty as more female-represented if its share of females is above the overall proportion.

Appendix D: Exceptions to the Standard Allocation to Internships

This appendix describes exceptions to the standard allocation of internship positions after the administration of the random lottery.

Special considerations: Students who can prove having serious health or social problems that require treatment where they live may receive priority in allocation. Specifically, this means that students can apply for special consideration only if they can provide documents indicating either that: (1) they or their immediate family are seriously ill and that treatment, care, or problems associated with this condition require special consideration; or that (2) their process of completing basic clinical training could lead to very serious social problems specified in a well-defined list. In practice, the National Health Authority grants this priority to less than 2% of each cohort. Consideration of spouses' attachment to workplaces or children's attachment to schools do not provide a justifiable cause.

Registered Couples: Couples can enter the lottery as a single entity and thereby draw a lottery number jointly, but only if there is a maximum of six months between their graduation dates. If the relationship dissolves after their request and prior to the allocation, the couple is still tied together in terms of the process. This maintains the validity of the gender-specific analysis.

Exchanging positions: After the final allocation of positions (so that the validity of the instrument is maintained), students are allowed to swap positions within 3-4 weeks. Nonetheless, the National Health Authority states in official guides ("Vejledning om tilmelding til turnusordningen"') that this option is rarely exercised.