The physicians' gender gap:

Evidence from Randomized lotteries

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Abstract

A random assignment of recently graduated physicians to their first job— through a nationwide public service program in Colombia — provides a test for sex-biased hiring. Using administrative data from the program, I find that the random assignment to the first job increases both the probability of a woman being hired and her earnings up to 5 years after the program. This document provides evidence that one of the main channels at work is the positive effect on the probability of access to graduate clinical programs. The evidence suggests that the random assignment to the first job fostered impartiality in hiring and access to graduate degrees.

Keywords: Gender gap, physicians labor market, experimental evidence.
JEL Codes: J44, J7, I28

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1 Introduction

A rich literature in economics has documented persistent gender gaps in wages in a broad range of contexts. In particular, there is substantial evidence of gender wage gaps in several occupations (Azmat and Ferrer, 2017; Goldin and Katz, 2016; Lo Sasso et al., 2020) and on the underrepresentation of women in top professions such as financial and corporate management (Bertrand et al., 2010; Bertrand and Hallock, 2001), academia (Bagues et al., 2017; Card et al., 2020; Ceci et al., 2014), political committees (Beaman et al., 2009; Chattopadhyay and Duflo, 2004), and top specialties in medicine (Zeltzer, 2020).

Despite large advances for women in the field of medicine over the past decade, important sex disparities still exist. The number of women in medicine has grown rapidly since 1970. Women now compose half of all US medical school graduates; however, women remain underrepresented in several areas of medicine. While they hold 38% of faculty positions in US medical schools, fewer than 19% of full professors are women (Association of American Medical Colleges, 2012). Besides, the physicians' earnings gender gap in the US was $56,019 (25.3%) between 2006-2010 (Lo Sasso et al., 2020).[1]. Furthermore, women are considerably underrepresented in surgical specialties compared to nonsurgical specialties.

A large literature has focused on physicians' gender gaps; however, part of the wage gap has remained unexplained. Most of the literature has been focused on hours worked, maternity, marital status, and specialty to explain the gaps (Esteves-Sorenson and Snyder, 2012; Lo Sasso et al., 2020, 2011; Ly et al., 2016; Sasser, 2005; Seabury et al., 2013; Weeks et al., 2009)[2].

Another well-known strand of the literature suggests that discriminatory employment policies are one of the key explanations for this phenomenon (Bertrand and Mullainathan, 2004; Goldin and Rouse, 2000). A fundamental question in this literature concerns how these policies affect the early career experiences of young female workers. Discrimination in the hiring of young workers occurs because employers may rely on characteristics such as gender as a proxy for individuals' productivity (Bardhi et al., 2020). Bias in hiring practices is extremely difficult to prove, and few researchers have been able to directly address this issue. An ideal experiment to study the above-stated concern would randomly assign workers

[1]In Italy, once differences in characteristics are controlled, women physicians earn 18 percent less than men (Gaiaschi, 2019). In Brazil, the probability of physicians' men receiving the highest salary level (>US$10,762) is 17.1% and for women physicians it is 4.1% (Mainardi et al., 2019)

[2]Some studies have focused on medical academy (Ash et al., 2004; Jagsi et al., 2012; Kaplan et al., 1996), where wage and representation of women in academic positions are mainly explained by the number of publications, hours worked and seniority in a faculty.

to their first job in relatively homogeneous firms with pre-established firm wage policies.

A large-scale random assignment of recently graduated physicians in Colombia provides an exceptional test for discriminatory hiring policies at the beginning of the physicians' professional careers. This is an unusual way to test the effects of sex-biased hiring practices. Two characteristics make this setting particularly interesting. First, Colombian regulations require recent graduates in medicine to work during the first year of their career in the national Mandatory Social Service program (SSO for its acronym in Spanish). In particular, during 2013 and 2014, the SSO program randomly assigns recently graduated physicians to small hospitals across the entire country. In addition, the wage policies of the hospitals that participated in the program were set prior to random assignment.

In this paper, I provide evidence on the causal effects of the SSO program. The random assignment of physicians to their first job in small hospitals, together with pre-set hospital wage policies, allow me to study the importance of hiring practices in the first and subsequent years of women physicians' careers. I provide experimental evidence on the effects of the SSO on a wide variety of outcomes. The core specification measures the change in a woman's outcome variable if she is selected through the program's lotteries, relative to her not being selected by the lotteries. The main results are threefold. First, I show evidence that up to three years before the SSO program, labor market outcomes, including the likelihood that a female is hired and her wages, are precisely zero effects, while the in-year impacts are positive and significant. Second, I follow SSO participants for over 5 years after the first draw to show that the main impacts are sustained in the medium-term. Finally, in addition to the labor market effects, I present the effects of the program on a wide range of outcomes including postgraduate decisions, and health outcomes.

In particular, I find that SSO lotteries increase in 9.45% the probability a woman be a formal worker in the first year of her career (7.5 percentage points (pp) increase) and 5 years after the program the effect increases up to 9.45% percent. Similarly, female lottery winners have higher earnings during the SSO program, and 5 years after the start of the program, the effect is 11.70% percent larger than women lottery losers. To shed light on the potential channels through which the program itself can impact physicians' gender gaps labor outcomes, I analyze the effects on postgraduate degrees; I found that women who participate in the program are 38.7% more likely to be enrolled in a postgraduate program 5 years after the program. Moreover, I analyze health outcomes and I do not find any effect on health outcomes including the probability of being pregnant, work-related illness and stress. Finally, I analyze several heterogeneous effects 4 years after the program across different physicians' characteristics.

An advantage of this setting is the availability of granular administrative data that runs up to December 2019 and includes information on the formal labor market, graduate school access and graduation, and health outcomes. The administrative records come from five sources. First, I collect data on the reports published by the Minister of Health of Colombia after SSO lotteries (Ministry of Health, 2014). I complement this data with the National Registry of Human Resources in Health, known as RETHUS (Ministry of Health, 2019b), which provides information on the date of graduation from any medical residency or postgraduate program. Then, I collected all the socioeconomic characteristics and the exit exam scores of the physicians on the SABER PRO database (Colombian Institute for Educational Evaluation, 2014). Third, I linked all physicians that participated in the SSO program with the Unified Register of Social Contributions in Colombia, known as PILA (Ministry of Health, 2019a), which contains mandatory contributions to health and pensions for all employees in the country. Finally, I merge the SSO program participants with the Individual Registry of Health Services, known as RIPS (Administrative Department of Statistics, 2018).

The identification strategy and the availability of granular administrative records allow this document to contribute to several strands of the literature. First, the findings contribute to the causal literature on discrimination in hiring practices (Bertrand and Duflo, 2017; Bertrand and Mullainathan, 2004; Kaas and Manger, 2012; Neumark, 2018; Petit, 2007; Riach and Rich, 2002; Weichselbaumer, 2004). In particular, this document relates to Goldin and Rouse (2000), who show that blind auditions increase the probability that a woman is hired.

This research is also related to the literature that studies gender gaps on the first job (Azmat and Ferrer, 2017; Bertrand et al., 2010; Kamas and Preston, 2015; Manning and Swaffield, 2008; Niederle and Vesterlund, 2007; Reuben et al., 2015) and the importance of the career path on the wage differentials (Bardhi et al., 2020; Flory et al., 2015; Light and Ureta, 1995). Finally, I add to the literature on the gender gap in the physicians' market (Buddeberg-Fischer et al., 2010; Esteves-Sorenson and Snyder, 2012; Fadlon et al., 2020; Jena et al., 2016; Lo Sasso et al., 2020, 2011; Sasser, 2005; Zeltzer, 2020).

The rest of the paper is structured as follows. Section 2 describes the physicians' training and regulations. Section 3 describes the experimental set-up, while section 4 describes and previews the data. Section 5 provides the empirical strategy. Section 6 presents the main estimated effects and briefly discusses potential mechanisms, and Section 7 concludes.

2 Physicians' Training and Regulations

Practicing medicine in Colombia today involves 6-7 years of training, including 1 year of practice or internship. All students who have completed their high school education can enroll in these programs. The completion of the curriculum leads to the title of a physician. Before graduation, all students are required to take the state test – SABER PRO. Upon completion of the final year of medical school and the state test, the graduate is required to complete the SSO period, mostly completed in rural areas. Once this requirement is certified, the aspirant receives a medical license that allows them to practice medicine.

In Colombia, medical specializations (surgical or clinical) have a treatment equivalent to master's degrees. These are formal postgraduate education programs that allow the physician to acquire in-depth knowledge of a specific area of medicine as set out in Decree 1665/2002. In the same decree, it is determined that the medical-surgical specialization programs will be developed exclusively with a full-time dedication by the students. The system for the admission of students to the medical specialization programs is done individually by each university; however, the State has defined as a strict admission requirement the fulfillment of the Obligatory Social Service which is at the same time an indispensable requirement to have a license to practice medicine in Colombia.

There is a high return on completion of specializations, but there are also high costs of access. This is a major difference between the medical education market in developed and developing countries. In the United States, the salary of a resident is approximately 40,000 dollars a year. In Colombia, in 2108, it was established that the salary of a resident would be less than 10,000 dollars a year and tuition could only be financed for approximately 700 dollars, which corresponds to 3 legal minimum wages per month. Before 2018, students did not receive any salary or financial aid. Moreover, students who enter a medical specialization must have exclusive dedication, that is, they cannot work while studying, additional to the high financial costs transferred to the student through tuition. This means that only a specific group with economic capacity has access to specialization programs.[3] The standard specialization program last 4 or more years and the physician must compete for the few available positions. Between 2007 and 2012, before the SSO program, 109,440 students

[3] The medical specializations in Colombia are programs that allow the doctor to acquire in-depth knowledge in a specific area of clinical medicine; they last from 3 to 5 years. The resident performs activities typical of the educational training cycle but also performs activities typical of the work cycle. The activities of both cycles are supervised by two types of institutions: Health Service Provider Institutions (IPS for its acronym in spanish) and Higher Education Institutions (IES for its acronym in spanish). Colombia is the only country in the world where national residents pay instead of receiving remuneration.

subscribe to compete for 7,379 seats in medical specializations programs.[4]

3 Program Design

The current Mandatory Social Service, known as the SSO program, was established by Law 1164/2007, and regulated by Resolution 1058 of 2010. Given the number of medical graduates in 2007 increased, the positions available for the SSO were less than the number of applicants. Therefore, how applicants were chosen and to which hospitals they were assigned became one of the program's most critical decisions. In that sense, the objective of Law 1164/2007 was to have an assignment "guided by the principles of transparency and equal conditions for all applicants". Following Resolution 1058 of 2010, it was established that decisions regarding who is selected and for which places, must be made through random drawings at the state-level.

A more organized way of performing random assignments was introduced at the end of 2012. The first years of the implementation of the new SSO program showed that the specifications given by Resolution 1058 of 2010 were not strong enough to ensure a transparent and organized assignation of physicians. For this reason, Resolution 4503/2012 was introduced to provide more clarity and more organized instructions on how the randomization should be done. Resolution 566 of 2012 mandated that beginning in January 2013 there would be 4 annual SSO drawings where each state would randomly assign professionals to all available positions in their territories from among the professionals that applied to each specific state.

Social service at the assigned hospitals begins about a month and a half after the drawing and lasts 12 months. If a health professional refuses to work in the place to which they were assigned or unilaterally leaves before the official end of the service, they are sanctioned with 6 months in which they cannot work as health professionals. After that period, they must apply to the SSO program again.

4 Data

The empirical analysis relies on reports published by the Ministry of Health for each department-level lottery for 6 randomizations in January, April, July, and October of 2013 and April, and July of 2014. From this database, I obtain information on the individual unique iden-

[4] Sistema Nacional de Información de la Educación Superior. (n.d.). Retrieved July 29, 2020, from https://snies.mineducacion.gov.co/portal/ESTADISTICAS/Bases-consolidadas/

tifiers of the participants (winners or losers), the date of the lottery, the state in which the applicant registered, whether the participant won the lottery, in which hospital was selected to provide social service and the start date.

Administrative records on formal sector earnings— The main data source is the Unique Registry of Health, Pension, and labor insurance Contributions, known as PILA, provided by the Colombian Ministry of Health. Firms with at least one paid employee are required to submit information on mandatory payroll components as health, pensions, and labor insurance on a monthly frequency. PILA has detailed information on earnings, firm and worker identifiers, and some demographic data. In PILA, I can track all firms in which the entire labor market of physicians worked. The Ministry of Health has universal coverage of all monthly contributions in the country since 2009, which gives me the possibility to track all those healthcare employees from 2009 to 2019.

National Registry of Human Resources in Health— The second source of information is the National Registry of Human Resources in Health, known as RETHUS. RETHUS was designed by the Ministry of Health, through the Law 1164 of 2007. RETHUS registers all individuals authorized to practice a profession or occupation in health. This data contains detailed information on the date of degrees, the date on which the medical license was granted, and postgraduate degrees.

SABER PRO— This dataset corresponds to the mandatory college exit exam that all professionals, including physicians, must take before graduation. Sociodemographic information at the individual level is obtained from this data provided by the Colombian Institute for Educational Evaluation (Spanish acronym, ICFES). Using scores and demographic characteristics from the SABER PRO, I show that the lotteries are well balanced between winners and losers. Table A.1 shows individual regressions between the lotteries and physicians' characteristics. In addition, Figure A.1 uses a classification permutation test to provide evidence on the equality of distributions between treated and non-treated physicians (Gagnon-Bartsch and Shem-Tov, 2019).

Individual Health Care Records— To explore health outcomes, I use information on Individual Health Care Records, known as RIPS from 2010 to 2019. This system of the Ministry of Health contains information on all procedures and services provided by the health entities and information on the user who receives them. Based on the identification number in the sample of physicians, I can match this information allowing me to track pregnancies and health conditions from 2010 to 2019.

Table 1 shows the summary statistics for the main outcomes used from PILA, RETHUS and RIPS. It also shows the differences between males and females used in the estimations. Column (1) shows the average for all the physicians in the whole sample, Column (2) shows the same statistic for the women and finally, Column (3) shows the average for men.

5 Empirical Strategy

The empirical setting exploits the variation associated with physicians, and random assignments to estimate the gender effects in a double difference strategy. In this setting, physicians were randomly assigned to the first job. The main empirical strategy estimates the impact of gain the lottery on a women's outcome (e.g., formality, wages, health), using the following linear specification:

$$y_i = \alpha_0 + \boldsymbol{\beta}_1 \text{Lottery}_i * \text{Female}_i + \beta_2 \text{ Lottery } + \beta_3 \text{ Female }_i + \phi_d + X_i'\gamma + u_i \tag{1}$$

where y_i is the outcome of women i. The coefficient $\beta_{\mathbf{1}}$ associated with the interaction of $\text{Lottery}_i * \text{Female}_i$ is the effect of interest. I also include fixed effects for draw date by state ϕ_d and control for the individual covariates in Table A.2. The coefficient on Lottery_i reveals whether the random assignments change the outcomes of all physicians. The standard errors are clustered by draw date-state. The identification assumption is that in the absence of treatment, the difference between treatment and control individuals is constant over the group (gender).

The causal interpretation of β_1 relies on the assumption that conditional on ϕ_d, the assignment was indeed random, then I verify empirically that the lotteries are uncorrelated with any observable of the physicians (see Table A.1). I focus on formality and earnings as the principal measures of the effects of the lotteries on women. Then I estimate the effects on graduate degree and health as potential mechanisms. Formality is defined as a binary variable that takes the value of 1 if the physician has a formal job and zero otherwise. Earning is defined as the total monthly real salary obtained by physician.

I also explore outcomes such as days worked, defined as the total number of days worked by physician. Number of jobs is a variable that counts the number of firms in which the physician worked. Enrolled postgraduate is a binary variable that takes the value of 1 if the physician is pursuing a postgraduate degree and zero otherwise. Graduated postgraduate is a binary variable that takes the value of 1 if the physician had already finished the postgraduate

Table 1: Summary statistics - physicians in the main sample

—	(1) All	(2) Women	(3) Men
Formality	0.499	0.528	0.460
	(0.314)	(0.296)	(0.333)
Earnings	1,559,328	1,606,848	1,494,647
	(1,204,688)	(1,128,288)	(1,299,089)
Days worked	162.670	170.965	151.380
	(102.989)	(97.020)	(109.626)
Number of jobs	0.554	0.574	0.527
	(0.368)	(0.341)	(0.401)
Enrolled postgraduate	0.051	0.049	0.054
	(0.130)	(0.127)	(0.135)
Graduated postgraduate	0.006	0.006	0.007
	(0.025)	(0.025)	(0.026)
Surgical postgraduate	0.001	0.001	0.002
	(0.011)	(0.009)	(0.013)
Clinical postgraduate	0.005	0.004	0.005
	(0.022)	(0.022)	(0.022)
Other postgraduate	0.000	0.000	0.000
	(0.007)	(0.007)	(0.006)
Pregnancy	0.017	0.028	0.001
	(0.053)	(0.067)	(0.012)
Consultations	0.334	0.383	0.267
	(0.248)	(0.253)	(0.225)
Laboral diseases	0.010	0.011	0.009
	(0.036)	(0.037)	(0.034)
Stress	0.012	0.013	0.011
	(0.053)	(0.054)	(0.051)

Notes: This table reports the summary statistics for the outcomes of the physicians included in the main sample. Formality is defined as a binary variable that takes the value of 1 if the physician has a formal job and zero otherwise. Earning is defined as the total monthly real salary obtained by physician. Days worked is the total number of days worked by physician. Number of jobs is a variable that counts the number of firms in which the physician worked. Enrolled postgraduate is a binary variable that takes the value of 1 if the physician is pursuing a postgraduate degree and zero otherwise. Graduated postgraduate is a binary variable that takes the value of 1 if the physician had already finished the postgraduate program and zero otherwise. Graduated postgraduate is a binary variable that takes the value of 1 if the physician had already finished the postgraduate program and zero otherwise. Clinical postgraduate is a binary variable that takes the value of 1 if the physician is pursuing or already finished a clinical postgraduate and zero otherwise. Pregnancy is a binary variable that takes the value of 1 if the physician has a pregnancy and zero otherwise. Consultations is a variable that counts the number of doctor's appointments. Occupational diseases is a binary variable that takes the value of 1 if the physician has been to a doctor's consultation because of occupational diseases. Stress is a binary variable that takes the value of 1 if the physician has been to a doctor's consultation because of a stressful condition and zero otherwise. The standard deviation of the outcome is presented in parenthesis.

program and zero otherwise. Graduated postgraduate is a binary variable that takes the value of 1 if the physician had already finished the postgraduate program and zero otherwise. Clinical postgraduate is a binary variable that takes the value of 1 if the physician is pursuing or already finished a clinical postgraduate and zero otherwise. Pregnancy is a binary variable that takes the value of 1 if the physician has a pregnancy and zero otherwise. Consultations is a variable that counts the number of doctor's appointments. Occupational diseases is a binary variable that takes the value of 1 if the physician has been to a doctor's consultation because of occupational diseases. Stress is a binary variable that takes the value of 1 if the physician has been to a doctor's consultation because of a stressful condition and zero otherwise.

I estimate equation 1 using characteristics included in X_i' as controls (see Table A.2). As expected, the estimations are robust to controlling for distinct groups of characteristics.

6 SSO program effects on female physicians

This section describes the causal effects of SSO lotteries on women's outcomes. First, I test whether random assignments have effects on labor market outcomes. I find that SSO lotteries have positive and significant effects on the probability a woman be a formal worker and the earnings in the first year of her career as well as 5 years after the program. The effects are also positive and significant for other labour market outcomes such as number of worked days per year and average number of jobs. Second, I find that the assignment causes gains on the probability of being enrolled in a postgraduate program and graduated in a post graduated program 5 years later. Third, I do not find any effect on health outcomes including the probability of being pregnant, work-related illness and stress. Finally, I estimate some heterogeneous effects.

6.1 Labor market effects

In this section, I provide the main results on labor market outcomes. Table 2 presents the average estimated coefficient β_1 in equation 1 for the whole period where I have data available (i.e. up to 5 years after the beginning of the program), using ordinary least squares. The coefficient represents the effects of a woman being assigned to the lottery relative to her not being selected on outcomes such as formality, earnings, worked days and number of jobs. The standard error of the coefficient is presented in parenthesis. Column (1) of Table 2 shows that there is a positive relationship between the woman being assigned to the lottery and the probability of being formal 5 years later—an increase in the probability of being formal in the next 5 years of 7.5 percentage points. The results suggest that being a woman assigned to the lottery increases the probability of being formal by 9.45% relative to her not being selected. Panel A of Figure 1 shows the estimated effects separated year by year. I do not find concerning evidence of pre-trends in the three previous years. In the first year of treatment, the effect is almost 8 percentage points and keep stable for the next 4 years. The largest effect occurs 5 years later (almost 13 percentage points).

Columns (2) to (4) in Table 2 examine other measures of labor market outcomes. The point estimate for the assignment to the lottery is associated with an increase in the monthly earnings of $448,000 (11.7% relative the the women's control mean), days worked in 27.64 (9.8%) and an increase in the number of jobs of 0.144 (13.1%). Panels B to C of Figure 2 show a dynamic behavior of the effects which is consistent with those found in formality. The results are robust to the inclusion of ex-ante individual characteristics as well as a vector of household and university characteristics (see Table A.3).

6.2 Postgraduate effects

A better understanding of the mechanisms through which graduate education is associated with the gender gap may influence where targeted efforts should be focused. Some studies had contributed to the analysis of the linkages between gender gaps and differences in graduate degrees (Goldin, 2014; Goldin et al., 2006; Montgomery and Powell, 2003; Morgan, 2008). However, the literature exploring the completion of those as a potential mechanism for closing the gender gap is sparse, even more in the physicians' market. Some literature had argued that a woman with an advanced degree may confront relatively less sex bias in her work environment given that education, which is easily observed and provides a signal to the employer about a worker's ability (Montgomery and Powell, 2003).

Table 3 presents the estimated coefficient $\beta_{\mathbf{1}}$ in equation 1. Column (1) of Table 3 shows that there is a positive relationship between the woman being assigned to the lottery and the probability of a being enrolled in a postgraduate program of 5.5 percentage points—an increase of 38.73% relative to her not being selected. A more general definition of formality is one that includes an individual working in the formal labor market or studying in the formal education system. Figure 2 shows the estimated effect year by year on the probability of being enrolled in a health postgraduate or being formal. The dynamics of the effect are close to the dynamics of formality (Panel A of Figure 1). However, the point estimates on average are larger joining both outcomes. Similar to the results of formality, the largest estimated

Table 2: Effects of randomization on labor market outcomes

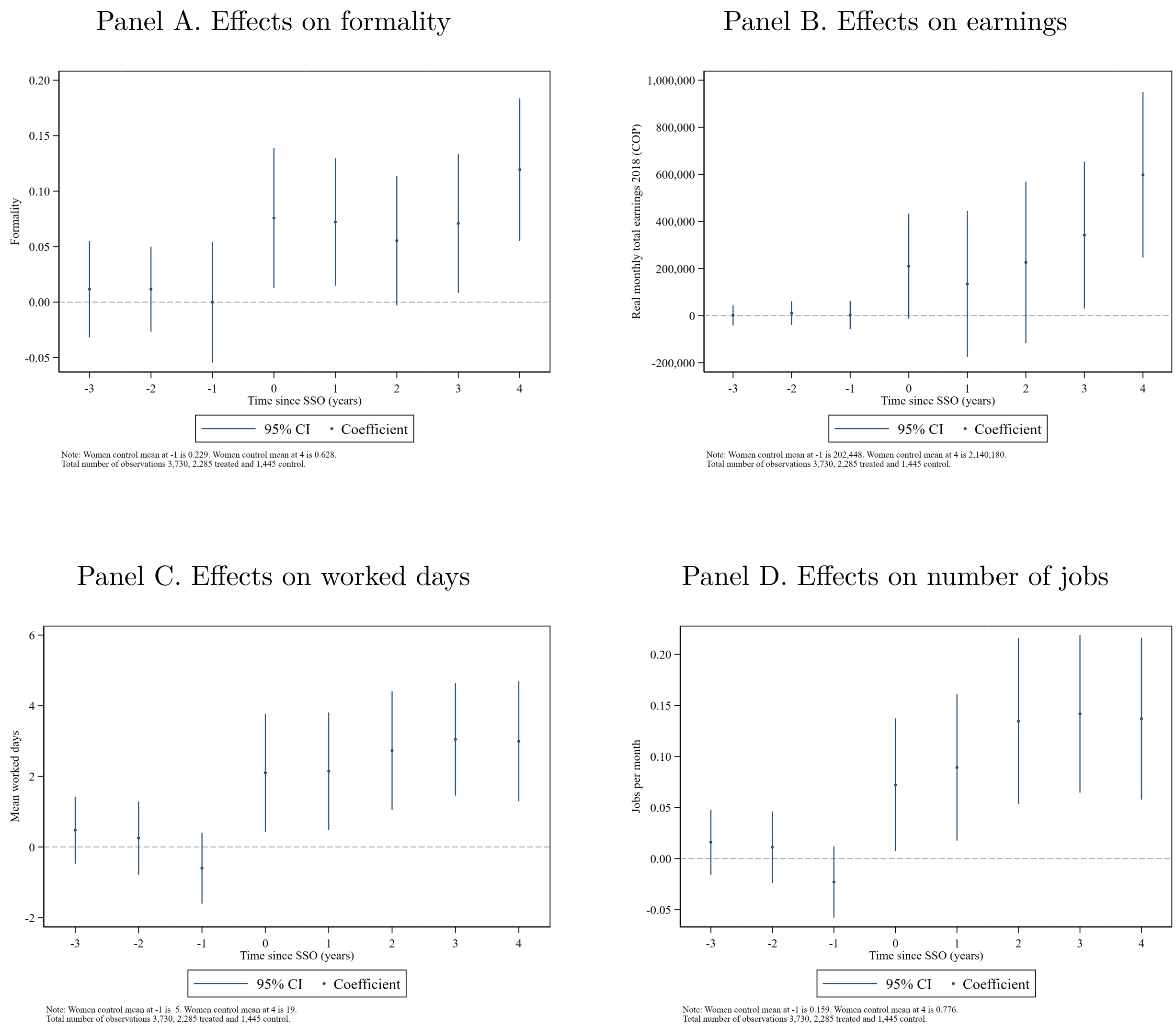
	(1) Formality	(2) Earnings	(3) Days worked	(4) Number of jobs
	Panel A. With controls			
Coefficient	0.075**	448,918**	27.64***	0.144***
Standard Error	(0.030)	(212,768)	(10.52)	(0.048)
Relative effect	9.45%	11.70%	9.80%	13.09%
	Panel B. Without controls			
Coefficient	0.074**	488,718**	27.36***	0.147***
Standard Error	(0.029)	(210,723)	(10.36)	(0.047)
Relative effect	9.32%	12.73%	9.70%	13.36%
Women control mean	0.794	3,837,703	281.96	1.1
Number of Observations	3,537			

Notes: Table 2 shows the main estimates. The coefficients represent the effect of a woman being assigned to the lottery, relative to her not being selected on each outcome. Relative (percent) effects are computed as the coefficient divided by the average of the women control mean. Formality is defined as a binary variable that takes the value of 1 if the physician has a formal job and zero otherwise. Earning is defined as the total monthly real salary obtained by physician. Days worked is the total number of days worked by physician. Number of jobs is a variable that counts the number of firms in which the physician worked. All regressions control for draw state fixed effects. Regressions for the coefficients labeled as "With controls" also include the controls in Table A.2. Numbers in parentheses are clustered standard errors. I interpret the high significance and consistency of these results across the different measures of labor market as evidence of the important role that the assignment itself can play on the physicians' gender gap. * significant 10%, ** significant 5%, *** significant 1%

point occurs 5 years later.

Columns (2) to (4) in Table 2 examine the probability of graduating from a graduate health program in our study period. The point estimate for the assignment to the lottery is associated with an increase in the probability of having a graduate degree in medicine of 4.6 percentage points (88.5%). Although we find effects on both surgical and clinical programs, the effect is mainly dominated by surgical programs. This is a ke results since these type of programs are usually dominated by males. I do not find significant effects on other postgraduate type of programs. The results are robust to the inclusion of ex-ante individual characteristics as well as a vector of household and university characteristics (see Table A.3).

Figure 1: Effects of randomization on labor market outcomes



Notes: Panels A to D of Figure 1 show the yearly coefficients and 95 percent confidence intervals from the estimation of equation 1 on the labor market outcomes. Formality is defined as a binary variable that takes the value of 1 if the physician has a formal job and zero otherwise. Earning is defined as the total monthly real salary obtained per physician. Days worked is the total number of days worked per physician. Number of jobs is a variable that counts the number of firms in which the physician worked. All regressions control for draw state fixed effects and also include the controls in Table A.2.

6.3 Health outcomes effects

In contrast to the literature on graduate degrees as a mechanism for gender gaps, the role of pregnancy and fertility decisions has been extensively studied (Angrist, 2002; Goldin and

Table 3: Effects of randomization on postgraduate outcomes

	(1) Enrolled postgraduate	**(2) Graduate postgraduate**	**(3) Surgical postgraduate**	**(4) Clinical postgraduate**	**(5) Other postgraduate**
			Panel A. With controls		
Coefficient	0.055**	0.046***	0.022**	0.025*	-0.0014
Standard Error	(0.026)	(0.015)	(0.009)	(0.013)	(0.004)
Relative effect	38.73%	88.46%	314.29%	62.50%	-20.00%
			Panel B. Without controls		
Coefficient	0.050*	0.042***	0.023***	0.020	-0.00036
Standard Error	(0.026)	(0.016)	(0.009)	(0.014)	(0.004)
Adjusted Coeff.	35.21%	80.77%	328.57%	50.00%	-7.20%
Women control mean	0.142	0.052	0.007	0.04	0.005
Number of Observations			3,537		

Notes: Table 2 shows the main estimates. The coefficients represent the effect of a woman being assigned to the lottery, relative to her not being selected on each outcome. Relative (percent) effects are computed as the coefficient divided by the average of the women's control mean. Enrolled postgraduate is a binary variable that takes the value of 1 if the physician is pursuing a postgraduate degree and zero otherwise. Graduated postgraduate is a binary variable that takes the value of 1 if the physician had already finished the postgraduate program and zero otherwise. Surgical postgraduate is a binary variable that takes the value of 1 if the physician is pursuing or already finished a surgical postgraduate and zero otherwise. Clinical postgraduate is a binary variable that takes the value of 1 if the physician is pursuing or already finished a clinical postgraduate and zero otherwise. All regressions control for draw state fixed effects. Regressions for the coefficients labeled as "With controls" also include the controls in Table A.2. Numbers in parentheses are clustered standard errors. I interpret the high significance and consistency of these results across the different measures of labor market as evidence of the important role that the assignment itself can play on the physicians' gender gap. * significant 10%, ** significant 5%, *** significant 1%

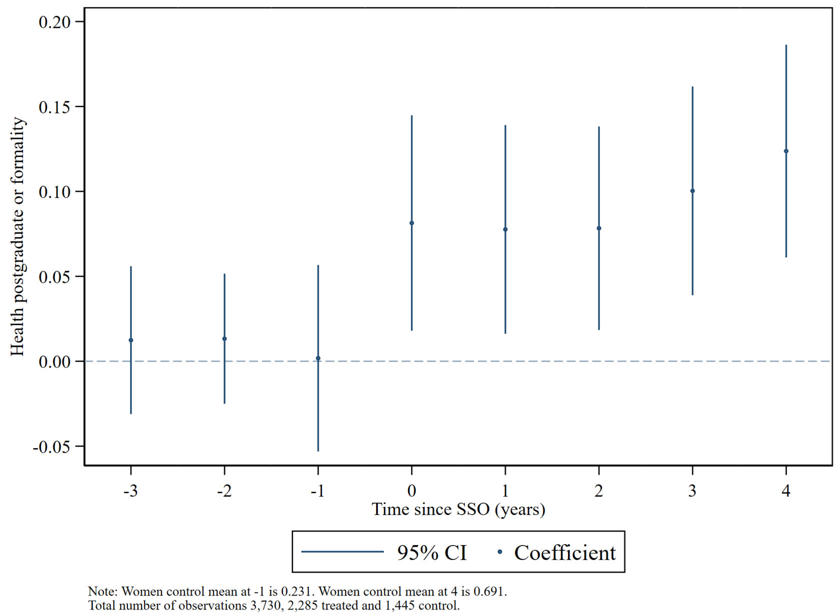
Katz, 2002).For instance, Jensen (2012) find that young women in randomized treatment villages in India were significantly less likely to have children during this period, choosing instead to enter the labor market or obtain more schooling training.

Table 4 shows that the points estimates are non-significant for the main outcome pregnancy. It seems that the pregnancy is not a potential mechanism to explain the positive effects of the SSO program on the labor market outcomes of woman physicians. In addition, I show that, although women lottery winners work more during and after the program, this do not have have any effect on general health outcomes such us consultations, but also in work related illness or stress. In Appendix Table A.5, I repeat the same regression and present the results for the inclusion of distinct set of controls such as individual characteristics, household characteristics and university characteristics; the results are robust.

6.4 Heterogeneous effects

So far I have analyzed the effects of SSO lotteries on several outcomes. I found that SSO assignment has positives and significant effects on labor market and a potential mechanism

Figure 2: Effects of lotteries on postgraduate or formality



Notes: Figure shows the yearly coefficients and 95 percent confidence intervals from the estimation of equation 1 on the labor market outcomes. Outcome is defined as a binary variable that takes the value of 1 if the physician has a formal job or is enrolled in a postgraduate program and zero otherwise. All regressions control for draw state fixed effects and also include the controls in Table A.2.

could be the enrollment to postgraduate degrees. To shed light on additional potential mechanisms through which the SSO lotteries may benefit female candidates, specifically on the wages gap, I explore whether assignment effects are more pronounced among some groups. The literature has emphasized in heterogeneous effects as geography, family structure, education and income (Kling et al., 2005; Roulet, 2020). In the physicians' context the literature had explored heterogeneous characteristics as specialty choice, practice setting and worked hours (Esteves-Sorenson and Snyder, 2012; Lo Sasso et al., 2020, 2011; Weeks et al., 2009)

I find that the effect of a woman being assigned to the program on formality is more pronounced among low skilled physicians (measured as being below the median of the distribution of the average test exit exam score, low household income, non-accredited university and non-top university (see Table 5). The differences are similar on earnings. In Panel C of Table 5, I show the effect of a woman being assigned to the program on being enrolled in a graduate degree. Similarly, the effect is more pronounced among low household income,

Table 4: Effects of randomization on health outcomes

	(1) Pregnancy	(2) Consultations	(3) Occupational diseases	(4) Stress
	Panel A. With controls			
Coefficient	-0.008	0.023	-0.003	0.002
Standard Error	(0.023)	(0.025)	(0.016)	(0.019)
Relative effect	-5.23%	2.84%	-3.53%	3.45%
	Panel B. Without controls			
Coefficient	-0.011	0.020	-0.010	-0.002
Standard Error	(0.022)	(0.027)	(0.016)	(0.018)
Relative effect	-7.19%	2.47%	-11.76%	-3.45%
Women control mean	0.153	0.811	0.085	0.058
Number of Observations	3,537			

Notes: Table 2 shows the main estimates. The coefficients represent the effect of a woman being assigned to the lottery, relative to her not being selected on each outcome. Relative (percent) effects are computed as the coefficient divided by the average of the women's control mean. Pregnancy is a binary variable that takes the value of 1 if the physician has a pregnancy and zero otherwise. Consultations is a variable that counts the number of doctor's appointments. Occupational diseases is a binary variable that takes the value of 1 if the physician has been to a doctor's consultation because of occupational diseases. Stress is a binary variable that takes the value of 1 if the physician has been to a doctor's consultation because of a stressful condition and zero otherwise. All regressions control for draw state fixed effects. Regressions for the coefficients labeled as "With controls" also include the controls in Table A.2. Numbers in parentheses are clustered standard errors. I interpret the high significance and consistency of these results across the different measures of labor market as evidence of the important role that the assignment itself can play on the physicians' gender gap. * significant 10%, ** significant 5%, *** significant 1%

non-accredited university and non-top university. However, contrary to the labor market outcomes, the probability of being enrolled in a postgraduate program is more pronounced among high skilled physicians.

Table 5: Heterogeneity of the effects across sets of characteristics

	Individual		Household		University			
	(1) High skilled	(2) Low skilled	(3) Household income: >2MW	(4) Household income: <2MW	(5) Accredited university	(6) Non-accredited university	(7) Top university	(8) Non-top university
Panel A. Formality								
Coefficient	0.073	0.123**	0.022	0.261***	0.017	0.103***	-0.002	0.101***
Standard Error	(0.067)	(0.058)	(0.036)	(0.072)	(0.039)	(0.039)	(0.045)	(0.035)
Relative effect	9.19%	15.49%	2.77%	32.87%	2.14%	12.97%	-0.25%	12.72%
Panel B. Earnings								
Coefficient	537,391	785,429**	351,904	911,553*	149,959	742,248***	-76,389	682,998***
Standard Error	(620,146)	(396,607)	(241,273)	(541,792)	(386,367)	(251,088)	(522,056)	(206,042)
Relative effect	14.00%	20.47%	9.17%	23.75%	3.91%	19.34%	-1.99%	17.80%
Panel C. Enrolled postgraduate								
Coefficient	0.127***	0.049	0.039	0.091**	0.079*	0.066**	-0.032	0.090***
Standard Error	(0.049)	(0.035)	(0.032)	(0.046)	(0.045)	(0.029)	(0.053)	(0.031)
Relative effect	89.44%	34.51%	27.46%	64.08%	55.63%	46.48%	-22.54%	63.38%

Notes: Table 1d shows the heterogeneity of the estimated results when I divide the sample by individuals, household and universities' characteristics. Relative (percent) effects are in square brackets and are computed as the coefficient divided by the average of the women's control mean. Formality is defined as a binary variable that takes the value of 1 if the physician has a formal job and zero otherwise. Earning is defined as the total monthly real salary obtained per physician. Enrolled postgraduate is a binary variable that takes the value of 1 if the physician is pursuing a postgraduate degree and zero otherwise. A physicians is considered to be high (low) skilled when the average test exit exam score was below the median. I consider accredited university as those universities that had the accreditation certificate by the Ministry of Education; the variable is split by the accreditation status of the physicians' college. Top (non top) university is defined with the QS World University Ranking; the variable is split by the ranking of the physicians' college. All regressions control for draw state fixed effects and the whole set of controls in Table A.2. Numbers in parentheses are clustered standard errors. * significant 10%, ** significant 5%, *** significant 1%

7 Conclusions

Decades of changes in social norms and implementation of anti-discrimination laws have contributed to improved levels of gender gaps, still, we continue to see gender differences in labor market outcomes (Card et al., 2016; Goldin et al., 2006). An extensive literature on labor market gender gaps has tried to explain the possible reasons for these differences today and in the past, the debate is ongoing (Duflo, 2012).

Despite a whole set of survey-based studies in medicine, and other occupations, there is a lack of causal evidence on the magnitude and potential mechanisms explaining these gaps on physicians. In this paper, I try to close this gap in the literature by exploiting random assignment of recently graduated physicians to their first job — through a nationwide public service program in Colombia — to provide a test for sex-biased hiring in the first job in medicine and its effects in the short and mid-term earnings and formality, and the likelihood of being attended a graduate degree in medicine or being pregnant as potential mechanisms. I take advantage of this randomization and Colombian granular administrative records to examine the causal impact of the assignment on several outcomes using unique newly graduated physicians' data.

In particular, I find that SSO lotteries increase in 9.45% the probability a woman be a formal worker in the first year of her career (7.5 percentage points (pp) increase) and 5 years after the program the effect increases up to 9.45% percent. Similarly, female lottery winners have higher earnings during the SSO program, and 5 years after the start of the program, the effect is 11.70% percent larger than women lottery losers. To shed light on the potential channels through which the program itself can impact physicians' gender gaps labor outcomes, I analyze the effects on postgraduate degrees; I found that women who participate in the program are 38.7% more likely to be enrolled in a postgraduate program 5 years after the program. Moreover, I analyze health outcomes and I do not find any effect on health outcomes including the probability of being pregnant, work-related illness and stress.

Finally, I analyze several heterogeneous effects 4 years after the program across different physicians' characteristics. I find that the effect of a woman being assigned to the program on formality and earnings is more pronounced among low skilled physicians (measured as being below the median of the distribution of the average test exit exam score, low household income, non-accredited university and non-top university.

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A Appendix

Table A.1: Balance

Covariable	Control mean	Standard Deviation	Coefficient	Standar Error	T-test	p-value (single hypothesis)
The household has a private car	0.483	0.500	-0.033	0.031	1.081	0.282
Number of people in the household	4.059	1.703	-0.126	0.138	0.912	0.363
Father with tertiary education	0.623	0.485	0.004	0.039	0.114	0.909
Mother with tertiary education	0.606	0.489	0.058	0.038	1.527	0.129
Socio-economic strata: 1, 2 or rural areas	0.268	0.443	0.025	0.030	0.842	0.401
Socio-economic strata: 4, 5 or 6	0.360	0.480	0.025	0.035	0.707	0.481
Level of Sisben: 1 or 2	0.246	0.431	0.006	0.032	0.199	0.842
The household has internet	0.847	0.360	-0.016	0.025	0.630	0.530
Monthly household income: Less than 2 MW	0.238	0.426	-0.042*	0.025	1.683	0.095
Monthly household income: $\geq$ 2 and $<$ 3 MW	0.212	0.409	0.013	0.039	0.333	0.740
The father or the mother have a job	0.872	0.335	0.023	0.025	0.900	0.369
The household has a washing machine	0.864	0.343	0.029	0.021	1.336	0.184
The household has a television	0.856	0.351	0.021	0.024	0.884	0.378
The household has a cellphone	0.968	0.176	0.019	0.014	1.366	0.174
Proper material of the floor in the household	0.919	0.272	0.018	0.020	0.909	0.365
The household has a oven	0.691	0.462	0.030	0.031	0.972	0.333
Score on the reading test (Saber Pro)	10.642	0.999	0.074	0.074	0.998	0.320
Score on the quantitative test (Saber Pro)	10.613	1.148	0.048	0.079	0.614	0.540
Score on the health care test (Saber Pro)	10.418	1.048	0.063	0.075	0.835	0.405
Score on the disease prevention test (Saber Pro)	10.446	1.022	0.055	0.067	0.827	0.410
Average on four SABER PRO scores	10.530	0.853	0.060	0.056	1.067	0.288

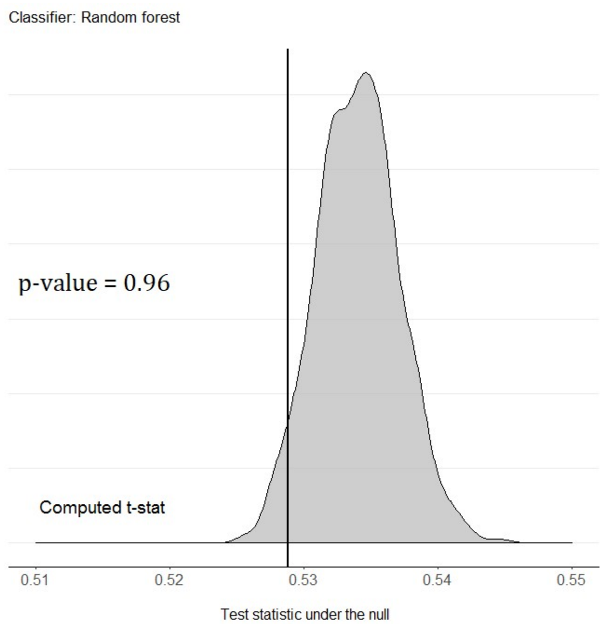
Notes: This table reports lottery losers' means and estimated effects of winning the SSO, based on a sample of 3,537 observations. Standard errors are clustered, given the by draw and state design of the randomization. Controls for draw-by-state fixed effects are included in the model. The eligibility for the subsidized regime is defined by the SISBEN score. SISBEN levels 1 and 2 are associated with the highest level of prioritization.

Table A.2: Summary statistics - physicians in the main sample

	(1) All	(2) Female	(3) Male
The household has a private car	0.502	0.517	0.480
	(0.500)	(0.500)	(0.500)
Number of people in the household	3.975	3.915	4.058
	(1.648)	(1.590)	(1.722)
Father with tertiary education	0.660	0.674	0.640
	(0.474)	(0.469)	(0.480)
Mother with tertiary education	0.656	0.680	0.623
	(0.475)	(0.466)	(0.485)
Socio-economic strata: 1, 2 or rural areas	0.243	0.212	0.285
	(0.429)	(0.409)	(0.451)
Socio-economic strata: 4, 5 or 6	0.403	0.426	0.372
	(0.491)	(0.495)	(0.483)
Level of Sisben: 1 or 2	0.231	0.197	0.277
	(0.421)	(0.398)	(0.448)
The household has internet	0.850	0.876	0.815
	(0.357)	(0.329)	(0.389)
Monthly household income: Less than 2 MW	0.216	0.192	0.248
	(0.411)	(0.394)	(0.432)
Monthly household income: $\geq$ 2 and $<$ 3 MW	0.206	0.196	0.220
	(0.405)	(0.397)	(0.414)
The father or the mother have a job	0.876	0.884	0.865
	(0.330)	(0.321)	(0.342)
The household has a washing machine	0.871	0.884	0.854
	(0.335)	(0.320)	(0.353)
The household has a television	0.867	0.892	0.833
	(0.340)	(0.311)	(0.373)
The household has a cellphone	0.967	0.971	0.961
	(0.179)	(0.166)	(0.194)
Proper material of the floor in the household	0.923	0.941	0.899
	(0.266)	(0.235)	(0.301)
The household has a oven	0.700	0.708	0.688
	(0.458)	(0.455)	(0.463)
Average on four SABER PRO scores	10.536	10.484	10.608
	(0.851)	(0.798)	(0.912)

Notes: This table reports the summary statistics for the controls of the physicians included in the main sample. The household has a private car if the household of the physician has a private car at the time the physician took the SABER PRO test and zero otherwise; Number of people in the household counts the number of individuals living in the same house as the physician; Father with tertiary education is a binary variable that takes the value of 1 if the physician's father has at least tertiary education and zero otherwise; Mother with tertiary education is a binary variable that takes the value of 1 if the physician's mother has at least tertiary education and zero otherwise; Socioeconomic strata: 1 or 2 or rural areas takes the value of 1 if the socioeconomic strata at the time the physician took the SABER PRO test was 1, 2 or rural and zero otherwise; Socioeconomic strata: 4, 5 or 6 is a variable that takes the value of 1 if the socioeconomic strata at the time the physician took the SABER PRO test was 4, 5 or 6 and zero otherwise; The household has internet takes the value of 1 if the physician had internet service at home at the time of the test; Monthly household income: Less than 2MW takes the value of 1 if the physician's household had an income lower than 2 minimum monthly wages and zero otherwise; Monthly household income: $\geq$2 and 3 MW takes the value of 1 if the physician's household had an income between 2 and 3 minimum monthly wages and zero otherwise; The father or the mother has a job, takes value 1 if either of the physician's parents have a job; The household has a washing machine, television, cellphone, proper flooring or oven, take value 1 if the household has that characteristic described and zero otherwise; Physician's average score on Saber Pro is the average of the four main components of the test, health care, disease prevention, reading and math.

Figure A.1: Balancing test using the permutation test (Gagnon-Bartsch and Shem-Tov, 2019)



Notes: This figure shows the results for the Classification Permutation Test (Gagnon-Bartsch and Shem-Tov, 2019). The procedure includes 1,000 repetitions. These result provide additional evidence in favor of the randomization

Table A.3: Labor market effects

	Women control mean	Women SSO effect				
		(1)	(2)	(3)	(4)	(5)
Formality	0.794	0.074**	0.077**	0.074**	0.072**	0.075**
	(0.405)	(0.029)	(0.031)	(0.029)	(0.028)	(0.030)
Monthly earnings	3,837,703	488,718**	467,669**	475,068**	475,007**	448,918**
	(2,801,650)	(210,723)	(215,634)	(211,088)	(207,864)	(212,768)
Daily earnings	133,762	17,396**	16,818**	16,947**	16,900**	16,163**
	(96,536)	(7,352)	(7,560)	(7,372)	(7,264)	(7,474)
Days worked	281.957	27.356***	28.164***	27.075***	26.467***	27.641***
	(144.556)	(10.360)	(10.857)	(10.207)	(10.063)	(10.520)
Number of jobs	1.101	0.147***	0.151***	0.143***	0.141***	0.144***
	(0.685)	(0.047)	(0.049)	(0.046)	(0.045)	(0.048)
Individual characteristics			x			x
Household characteristics				x		x
University characteristics					x	x

Table A.4: Postgraduate effects

	Women control mean	Women SSO effect				
		(1)	(2)	(3)	(4)	(5)
Enrolled postgraduate	0.142	0.050*	0.052*	0.049**	0.057**	0.055**
	(0.349)	(0.026)	(0.028)	(0.025)	(0.025)	(0.026)
Graduated postgraduate	0.052	0.042***	0.045***	0.041***	0.045***	0.046***
	(0.222)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)
Clinical postgraduate	0.040	0.020	0.024*	0.020	0.022*	0.025*
	(0.195)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)
Surgical postgraduate	0.007	0.023***	0.022**	0.023***	0.024***	0.022**
	(0.086)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Other postgraduate	0.005	0.000	-0.001	-0.001	0.000	-0.001
	(0.070)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Individual characteristics			x			x
Household characteristics				x		x
University characteristics					x	x

Table A.5: Health effects

	Women control mean	Women SSO effect				
		(1)	(2)	(3)	(4)	(5)
Consultations	0.811	0.020	0.023	0.024	0.014	0.023
	(0.392)	(0.027)	(0.026)	(0.025)	(0.025)	(0.025)
Pregnancy	0.153	-0.011	-0.008	-0.010	-0.013	-0.008
	(0.360)	(0.022)	(0.023)	(0.022)	(0.023)	(0.023)
Occupational diseases	0.085	-0.010	-0.004	-0.007	-0.012	-0.003
	(0.279)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Stress	0.058	-0.002	-0.001	0.001	-0.001	0.002
	(0.234)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
Individual characteristics			x			x
Household characteristics				x		x
University characteristics					x	x