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Gender pay gap in a highly qualified sector: evidence from administrative data*

Nina Giordano† Cecilia Parada‡ Mijail Yapor§

Abstract

This paper studies the existence of gender pay gaps within the highly skilled profession of medicine in Uruguay. We focus on understanding whether the way an occupation is structured may impact income equality. We use administrative data from the Human Resources Control and Analysis System (SCARH) database, published by the Ministry of Public Health of Uruguay. We estimate the gross and conditional gender pay gaps among physicians for the entire period between 2008 and 2018. Furthermore, we evaluated two potential mechanisms that could explain part of the differences in physician earnings, specifically horizontal segregation (the concentration of women in certain specialities with lower salaries) and vertical segregation (the under representation of women in top hierarchical positions). Our results indicate differences in labour income between female and male physicians, and that horizontal and vertical segregation play a role in explaining these gaps.

JEL Classification: J16, J24, J31, J7
Key words: gender pay gaps, highly prestigious occupations, physicians, segregation

Resumen

Este artículo estudia la existencia de brechas de género en los ingresos laborales dentro de la profesión médica, altamente calificada, en Uruguay. Nos centramos en comprender si la forma en que se estructura una ocupación puede afectar la igualdad de ingresos. Utilizamos datos administrativos de la base de datos del Sistema de Análisis y Control de Recursos Humanos (SCARH), publicada por el Ministerio de Salud Pública de Uruguay. Estimamos las brechas de género en el ingreso laboral brutas y condicionadas entre los médicos para todo el período comprendido entre 2008 y 2018. Además, evaluamos dos mecanismos potenciales que podrían explicar parte de las diferencias en los ingresos de los médicos, específicamente la segregación horizontal (la concentración de mujeres en ciertas especialidades con salarios más bajos) y la segregación vertical (la baja representación de las mujeres en los puestos jerárquicos más altos). Nuestros resultados indican diferencias en los ingresos laborales entre médicos mujeres y varones, y que la segregación horizontal y vertical desempeña un papel clave a la hora de explicar estas brechas.

Clasificación JEL: J01, J08, J3
Palabras clave: brecha de género en ingresos, ocupaciones de alta calificación, médicos, segregación

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1 Introduction

The participation of women in the Latin American labour market has grown significantly in the last half-century, with an increasing number of women entering highly prestigious occupations (Goldin, 2014). Nevertheless, despite this progress, differences in the outcome variables of men and women in the labour market persist, and the process of convergence has slowed since the 1990s (Goldin, 2014; Marchionni et al., 2019). Women display lower participation rates, work fewer hours, and earn less than men. Furthermore, the structure of female employment in Latin America is also gender-biased, with a high number of women working in social services such as education and health (Marchionni et al., 2019). Despite their improved employment-linked qualities, women's lower earnings persist. In particular, in Uruguay, Espino et al. (2014) find that labour income gaps remain even in the skilled population, showing that a higher educational level of women is not enough to eliminate gender differences in earnings.

The literature on gender gaps in the labour market is extensive, but there is a lack of research on what happens within specific occupations (Goldin, 2014). In particular, among medical workers, family factors have been suggested to be relevant in explaining women's decisions about how much to work. In this way, part of the wage gender gap is usually explained by the fact that women work fewer hours than men due to factors associated with gender norms (Frank et al., 2019; Ly and Jena, 2018; Carr et al., 2015). However, even controlling for hours worked, inequalities persist. This underscores factors linked to discrimination and work environment, preventing women to be equally rewarded as men or access leadership positions in the same way (Carr et al., 2017). We examine the existence of gender pay gaps within a highly skilled profession and understand whether the way an occupation is structured may impact income equality. Our aim is to investigate income disparities between male and female physicians in Uruguay. This sector exhibits a high level of female participation and a significant degree of qualification in a developing country. To address this question, we use data from the Human Resources Control and Analysis System (SCARH, for its acronym in Spanish), an administrative database published by the Ministry of Public Health. This registry contains information on workers in the private healthcare sector, including Collective Medical Assistance Institutions (IAMC - in Spanish) and health insurance, between the years 2008 to 2018. These records enable us to analyze the full spectrum of labour incomes earned by physicians employed in the private healthcare sub-sector.

We begin by estimating the gross and conditional gender pay gap among physicians for the entire period. Next, we evaluated two potential mechanisms that could explain part of the differences in physician earnings. First, given that physicians work in different specialities, the differences in earnings could be due to a higher concentration of women in those specialities with lower salaries. If female-dominated occupations have lower pay, the difference is greater, which is known as horizontal segregation. This concentration of women in certain specialities may be due to discrimination, preferences for specialities that have schedules and work patterns more compatible with family life, or differences in preferences and tastes (Magnusson, 2016). To determine the existence of horizontal segregation, we calculate the segregation indices Duncan and Duncan (1955) and Karmel and Maclachlan (1988) for each year of the sample. Additionally, we estimate the influence of horizontal segregation on the gender pay gap by applying a methodology proposed by Bayard et al. (2003) and we perform a detailed decomposition to quantify the contribution of each group of specialities to the overall gender pay gap.

Second, the under representation of women in top hierarchical positions could contribute to the gaps in the healthcare sector. Despite increasing education and experience for women, they are still underrepresented in higher-paid positions (Marchionni et al., 2019; Kunze and Miller, 2017). Therefore, we evaluate whether there are differences in the representation of women and men along the hierarchical scale that is transversal to the specialities, known as vertical segregation. A greater difference at the top of the distribution is known as a glass ceiling. This barrier explains a significant portion of the labour income gap, especially for the most educated workers. To study vertical segregation, we estimate quantile regressions based on the re-centered influence function (RIF) proposed by Firpo et al. (2009).

Our results indicate that there are differences in labour income between female and male physicians even after controlling for observable characteristics of the individual and the field of medicine, such as medical speciality. We do not observe a decrease in the conditional gap during this period. We found evidence that segregation by speciality contributes significantly to explaining the gender gap in physician earnings. Furthermore, our estimates are consistent with the presence of a glass ceiling for women in the medical sector.

This paper is integrated into the literature on gender gaps (Goldin, 2014; Blau and Kahn, 2017). A significant portion of this literature has focused on studying the importance of occupational segregation as a relevant component of the differences in labour income. In developed countries, it has been observed that occupational segregation, as well as differences within occupations and within firms, are important in explaining the labour earnings gap (Macpherson and Hirsch, 1995; Bayard et al., 2003; Ponthieux et al., 2015). In the US, the increasing importance of the income gap at the top of the distribution in the overall income gap has been documented (Blau and Kahn, 2017). The explanations found by the authors include temporary career breaks and shorter working hours for women (especially among high-skilled workers), gender roles and the resulting division of labor and occupational segregation, and the persistence of discrimination. In Latin America, the sectoral structure of the labour market differs by gender, and women tend to work in more flexible jobs than men in terms of the organisation of the working day. The hourly wage of a woman is on average 22 % lower than that of a man when workers with similar characteristics are compared (Marchionni et al., 2019). Although most of this gap corresponds to differences within occupations, there is evidence of the presence of a glass ceiling for women that would explain part of the differences in income by gender (Carrillo et al., 2014; Pal, 2019).

In Uruguay, studies have shown that gender discrimination in the labour market plays a role in explaining the income differences between men and women (Bucheli and Rossi, 1985; Furtado et al., 1998; Rivas and Rossi, 2002). More recently, Colacce et al. (2020) found that the gender pay gap is largely explained by the fact that women work fewer hours. However, the difference in hourly earnings between males and females with the same sociodemographic characteristics amounts to 19 %. Regarding the importance of segregation, some studies have found that female earnings are negatively affected by the concentration of women in certain occupations, while male earnings are not adversely affected by the same conditions (Amarante and Espino, 2004; Katzkowicz et al., 2013).

Occupational segregation and mismatches by qualification have also contributed to explaining a significant portion of the labour income gap in Uruguay (Espino, 2013; Espino et al., 2014). Particularly for wages, other studies have found that the conditional gender pay gap is more important in the upper percentiles of the wage distribution, suggesting the presence of a glass ceiling in Uruguay (Bucheli and Sanromán, 2004; Borrás and Robano, 2010).

We also add to a strand of literature that studies gender labour income differences in the health sector. Previous studies in developed countries have shown that there are earnings differences between male and female physicians that are not only due to their observable characteristics but also attributed to different factors such as different speciality choices (Dumontet et al., 2012; Magnusson, 2016), parenthood and marital status (Sasser, 2005; Magnusson, 2016), number of hours worked (Dumontet et al., 2012) and discrimination (Gravelle et al., 2011). For Latin America, evidence is scarce, but it has been observed in Peru (Amaya and Mougenot, 2019) and Argentina (PNUD, 2018) that female physicians have lower salaries than their male peers, which cannot be explained by their observable characteristics.

With this paper, we make three main contributions. First, we add to the analysis of gender pay gaps within a highly qualified profession in a developing country. Although the gender pay gap has been found for physicians professionals, most of the evidence is from developed countries (Theurl and Winner, 2011; Magnusson, 2016; Gravelle et al., 2011), and there is limited research in developing countries. To the best of our knowledge, this is the first study using administrative records that focuses on the health sector in Latin America.

Second, we contribute to the study of a particular profession that is interesting to explore. The labour market for physicians has characteristics that make it a noteworthy case study. Firstly, workers in the medical profession have relatively homogeneous qualifications, with the medical career being one of the longest in terms of years of study. This reduces the dispersion in unobservable variables such as investment in human capital and commitment to work among physicians. Secondly, in Uruguay, the health sector is characterised by high participation of female workers, a phenomenon that has increased recently (González Mora et al., 2018). However, there are gender-related differences in the type of positions held by workers, either among the different specialities or in the number of supervisory positions they hold.

Third, as the participation of female workers in the study universe showed an increase between 2008 and 2018, it is of interest to know whether this phenomenon is accompanied by an increase or decrease in the gender pay gap. This paper contributes to generating useful information for policymakers, both those responsible for training and employment, to guide the design of instruments that can correct gender inequality. Labour income is the main source of income for most populations, and the lower income received by women translates into a lower capacity to consume and make decisions on household spending, thus undermining their capacity for self-management and independence. Empowering the capabilities of the female population contributes to the economic and social progress of countries (Espino et al., 2014).

The remainder of the paper is organised as follows. Section 2 presents a description of the labour market of the health sector. Section 3 describes the database and the empirical approach. Section 4 discusses the results of the study, exploring some mechanisms that explain those results. Finally, Section 5 concludes.

2 Labour market in the healthcare sector in Uruguay

Uruguay's healthcare sector is divided into two sub sectors: private and public. Health workers often work in both sub sectors indistinctively. This section provides a brief overview of the labour market organisation within the healthcare sector, with a focus on the private sub sector. Specifically, it will cover the main healthcare institutions (known as IAMCs for its acronym in Spanish), and physicians.

2.1 Human Capital and Employment

To become a General Practitioner (GP) in Uruguay, a seven-year training program is required. Furthermore, obtaining the title of Medical Specialist as a GP requires an additional 3 to 6 years of training, depending on the chosen speciality. There are two options available to obtain a speciality: the Conventional Postgraduate Program and the Residency Program. However, there are limited quotas available for postgraduate or residency programs per speciality and per year (please refer to Table A.1 for more details). General practitioners are required to take one or more tests, and the allocation of these training quotas is dependent on their test results.

There are three differences between the Conventional Postgraduate Program and the Residency Program: The Residency Program is paid, has a greater time load, and requires full-time dedication. Some specialties can only be taken through Residency (this is the case of those with a high degree of manual training, such as surgery), others can only be taken through the Postgraduate Program, and others through both systems.[1]

Physicians in Uruguay are characterised by high multi-employment. Most of them have more than one job, which can be classified as public salaried, private salaried, self-employed, and employer (e.g., of a private clinic). As shown in Table 1 (and Table A.3), less than half of physicians have only one job in the private sector, which is reduced by 31 % when private and public sectors are considered. The multi-employment is slightly more important for men than women (50 % of women hold a single position in private institutions, while for men it is 45 %).

Cuadro 1: Multi employment of medical work in IAMCs in 2018

Number of positions	All Physicians	%	Women Physicians	%	Men Physicians	%
1	4,501	48 %	2,771	50 %	1,730	45 %
2	2,445	26 %	1,415	26 %	1,030	27 %
3	1,268	13 %	741	13 %	527	14 %
4	619	7 %	340	6 %	279	7 %
5	278	3 %	139	3 %	139	4 %
6	135	1 %	71	1 %	64	2 %
7 and more	151	2 %	48	1 %	103	3 %
Total	9,397	100 %	5,525	100 %	3,872	100 %

Source: SCARH.

The existence of several positions within the same sub sector is also illustrated by the relevance of substitutions (incumbent physicians overloaded with several jobs tend to make room for

[1] A detailed description of the medical residency market in Uruguay can be found in (Contreras and Faggetti, 2016).

substitute physicians frequently). There are even two types of substitute positions, permanent and non-permanent. In 2018, 46 % of mutualist positions were tenured, 40 % were substitutes, and 14 % were independent. In turn, within each position, there are different working modalities. Some examples are polyclinics, standby duty, and on-call duty. The modalities are different from each other in terms of working hours and each modality has different characteristics. [2] Table 2 shows the average number of hours worked per speciality group and per work modality.

Cuadro 2: Average hours worked per month by specialty group and by area at IAMC 2018

AREA	Directors / Chiefs	General Medicine	Pediatrics / Family	AS	MS	ICU / Internal Medicine	Pathologists / Radiologists	Residents
Polyclinic	0	19	24	16	25	4	28	33
Emergency	0	12	9	0	0	0	0	0
Home	0	4	1	0	0	3	0	0
Radio	0	6	7	0	1	0	0	1
On call	0	7	11	6	3	22	7	9
Puerta	0	24	22	2	0	7	1	5
On call Adult ICU	0	1	0	0	0	35	0	39
On call Paediatric	0	0	1	0	0	10	0	2
Holding	0	6	4	20	12	2	17	1
Sanatorium	0	3	3	4	7	13	13	47
Block	0	0	0	8	0	0	0	0
Others	0	4	3	3	5	3	15	52
Direction	109	0	0	0	0	0	0	0
TOTAL	109	84	84	58	55	99	80	189

Note: MS = Medical Specialities; AS = Anaesthetic and Surgical Specialities. The speciality groups were formed according to the modality of work. **Source**: SCARH.

In 2012, the New Medical Work Regime was approved, creating the High Dedication Positions (in Spanish CAD). In general, these positions imply an increase in the number of hours worked at the same institution, although they do not guarantee full-time work. Likewise, in many cases, a CAD implies an increase in the hourly value of the salary (but not in all cases, especially for specialities where payment per act is predominant). These positions were implemented gradually and by speciality. In the private sector, CAD positions predominate in general medicine, paediatrics, internal medicine, and intensive care medicine. In 2018, CAD positions came to represent 6 % of private sector positions (see Table A.4).

2.2 Salary

Uruguay has a collective bargaining system where wages for healthcare workers are negotiated among the government, employers, and workers. The salaries paid to physicians by mutual

[2]For example, in the case of *standby*, the physician is called to his or her place of work only if it is necessary for an emergency reason. The various medical specialities differ significantly from each other with respect to working arrangements.

insurance companies consist of two components: a fixed and a variable payment. The fixed payments refer to either a monthly or an hourly salary, while the variable payments are based on the number of times a service is performed. These services may be related to the number of patients seen or to the performance of a medical act, such as surgery or delivery of a baby. The level of remuneration for both fixed and variable payments is dependent on the type of activity performed and the medical speciality.

Table 3 shows the monthly average income, the number of hours worked, and the number of medical acts performed by physicians in the IAMCs. Income per medical act represents on average 24 % of total monthly income. This average hides important heterogeneities by speciality. Among the medical acts, there is an important distinction between those that are associated with another modality, for example, medical acts that are performed within the framework of polyclinic hours, and medical acts that are previously coordinated and of longer duration, such as surgery (block acts).

Cuadro 3: Income, hours worked and acts by position 2008-2018 (monthly average, constant uruguayan pesos 2018).

Year	Income (in Uruguayan pesos)			Hours per position	Medical act by position
	Total payments	Fixed payments	Variable payments		
2008	94,304	57,294	20,431	80	74
2009	90,484	55,180	20,548	76	72
2010	88,416	54,597	20,785	75	78
2011	92,820	57,366	22,598	76	89
2012	93,385	57,412	23,070	74	80
2013	96,964	60,508	23,274	74	76
2014	98,778	63,157	22,817	74	75
2015	101,490	64,828	23,632	75	80
2016	101,935	66,083	24,048	75	73
2017	102,829	66,013	24,768	74	70
2018	102,939	67,377	24,147	73	70

Source: SCARH.

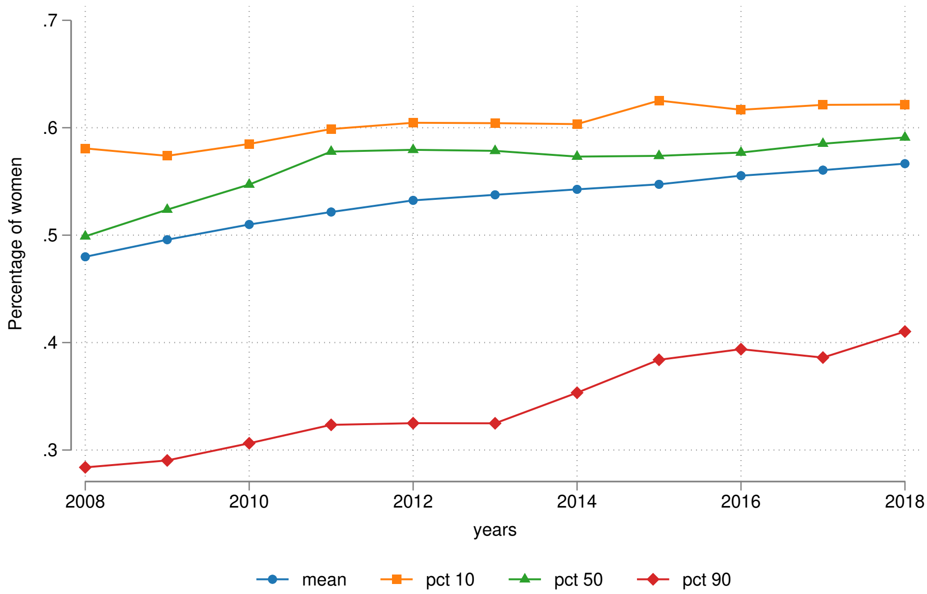
2.3 Women's participation

The healthcare sector has historically been feminised. Currently, this feminisation is transversal to the different occupations within the sector, e.g., medical staff, nursing, non-medical technicians, and administrative services and trades. In particular, the increase in women's participation among physicians is a phenomenon that has been occurring in recent years (González Mora et al., 2018). The number of women in total physician positions in IAMCs grew from 48 % to

57 % between 2008 and 2018 (Figure 1).

On the other hand, the participation of women decreases when we restrict the population to those receiving the highest incomes (Figure 1). In 2018, approximately 60 % of decile 1 (10 % lowest income) positions were held by women, while in decile 10 (10 % highest income) female participation is 41 %. Therefore, despite registering an improvement of more than 10 percentage points in the participation of women in the highest income brackets between 2008 and 2018, the existence of a glass ceiling in the sector continues to be perceived. At the same time, despite there being a majority of female physicians in the total number of physicians in IAMCs, women are underrepresented in management and chief positions and in surgical specialities (the highest-paid positions). In contrast, they are over represented in paediatrics and family medicine. This could be due to the fact that some specialities, such as surgical specialities, have barriers to entry for women, and that in the work-spaces these are less valued than males (González Mora et al., 2018).

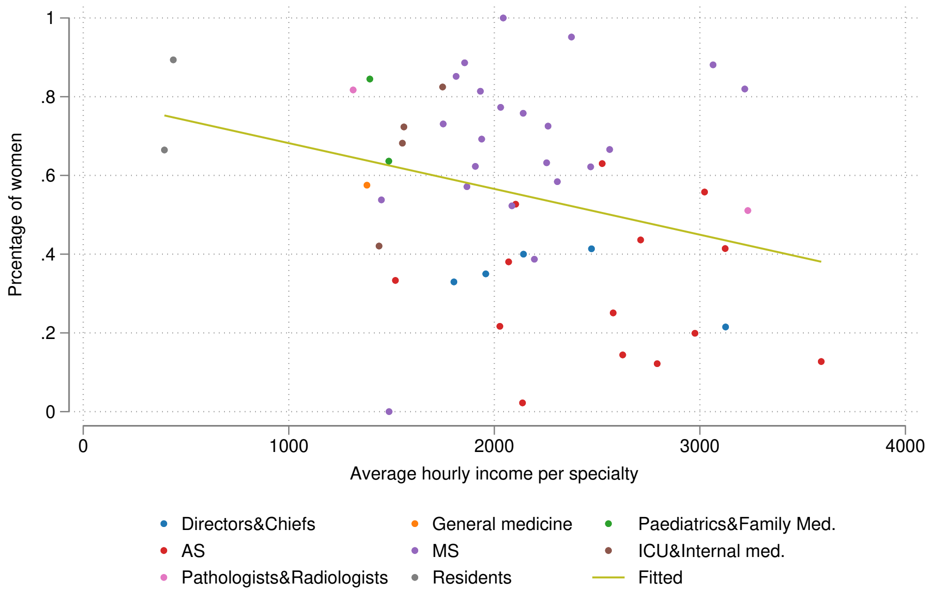
Figura 1: Percentage of women in total positions by year, 10th, 50th and 90th income percentile.



Note: The figure shows the proportion of female physicians in each decile of the monthly salary distribution. **Source**: SCARH.

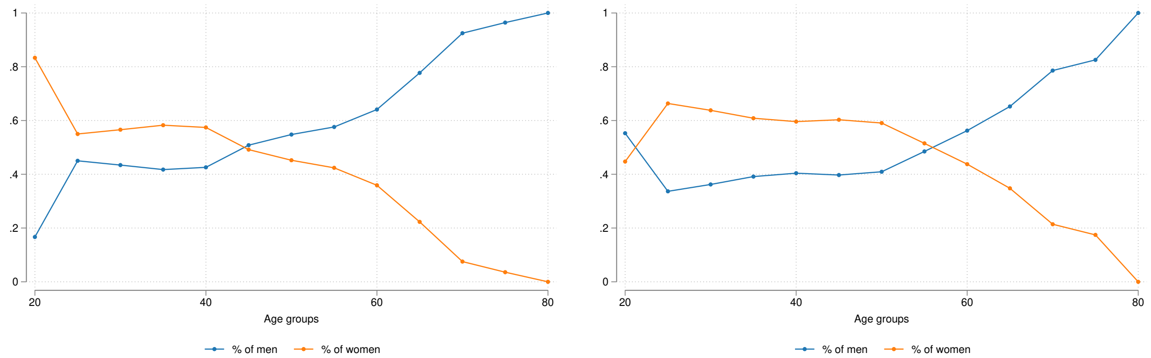
In addition, the authors raise the difficulty perceived by Uruguayan female physicians to reconcile their careers with family life. As a result, when observing the monthly hourly income and the percentage of women by speciality (Figure 2), a negative relationship between the two variables is perceived. In other words, women are employed to a greater extent in specialities with lower hourly incomes.

Figura 2: Percentage of women and average hourly income by speciality in 2018



Note: MS = Medical Specialties; AS = Anesthetic and Surgical Specialties. The specialty groups were formed according to the modality of work. Details of the specialty groups are shown in A.2. **Source**: SCARH.

Figura 3: Percentage distribution of medical positions by age and gender in 2008 and 2018.



(a) 2008

(b) 2018

Note: The figure shows for 2008 and 2018 the proportion of female and male physicians according to groups of age. **Source**: SCARH.

Finally, the age structure of men is older than that of women. Panels a) and b) of Figure 3 present the percentage of women according to groups of age in 2008 and 2018, respectively. In 2008, it can be seen that women are the majority in the younger population, up to the 45 to

50 age bracket. After that age, physicians are mostly male. In 2018, the difference occurred ten years later, between 55 and 60 years of age.

3 Empirical approach

3.1 Data

We use individual-level data from two sources: *Sistema de Control y Análisis de Recursos Humanos* (SCARH, for its acronym in Spanish) and *Infotítulos*. The SCARH database is an administrative registry, published by the MSP, and represents the main source of information for the present work. Contains data on health human resources in the private sector between 2008 and 2018, for the two main healthcare institutions (IAMCs and Seguros Privados). It includes monthly information on payments, hours worked, and acts performed by position, for February, May, August, and November of each year. It also contains information on the institution from which the position originates, the relationship of each position with that institution (substitutes, incumbents, independents), as well as demographic characteristics of the workers, such as gender and age. Physicians and other workers (as medical technicians, administrative staff, etc.) can be identified separately. A worker can have more than one position per institution and each position has an individual identifier code. In this paper, only data on medical positions are used for estimation purposes. To illustrate, we have information about 36,398 medical positions of different specialties in 2008, and 54,403 in 2018 (Table A.5).

The *Infotitulos* database, which is also published by the MSP, contains the accredited qualifications of the health labour force. According to the current regulations, the authorization of the MSP is mandatory for the practice of the profession.

3.2 Methodology

To investigate the existence of a labour income gap between male and female physicians we follow different approaches. First, we estimate augmented versions of the traditional Mincer equations. To further characterize these primary results, then we pursue several methodological strategies. Horizontal segregation is evaluated using segregation indices, and we estimate the contribution of this segregation to the gender gap, as suggested by Bayard et al. (2003). This analysis is supplemented by Oaxaca-Blinder decompositions. To assess the presence of vertical segregation, we use the unconditional quantile regression method proposed by Firpo et al. (2009). Additionally, we will conduct decompositions based on this quantile regression approach to uncover the mechanisms that account for the gender differences between and within medical specialities.

3.2.1 Gender gap

First, we estimate the (conditional) pay gender gap [3] by the following linear model:

$$ln(y_i) = \alpha + \beta female_i + X_i'\Lambda + \epsilon_i \tag{1}$$

Where $ln(y_i)$ corresponds to hourly or monthly income (in logs), $female$ is a binary variable with value 1 if the individual is a woman; X_i is an $n \times 1$ vector including several controls that account for other individual characteristics (quadratic in age, dummies for specialty, contract type, high dedication worker and health care institution, and hours worked and medical acts performed in the monthly case). The regression error term is ϵ_i.

3.2.2 Horizontal segregation

Second, to determine whether horizontal segregation exists, we calculate the Duncan and Duncan (1955) and Karmel and Maclachlan (1988) segregation indices (hereafter DI and KM, respectively) for each year of the sample. The methodological details of these indices can be found in Appendix B. We also investigate the influence of horizontal segregation on the labour income gap by applying the alternative proposed by Bayard et al. (2003). This method involves estimating a linear model in which wage differentials are a function of individual characteristics and the extent of feminisation in different work environments. In this case, feminisation is measured in two ways: as a percentage of women in the medical speciality and the institution.

The regression to be estimated is:

$$ln(y_i) = \alpha + \beta female_i + \gamma Fem.Spec_g + \delta Fem.Inst_n + X_i'\Lambda + \epsilon_i \tag{2}$$

Where variables are the same as equation (1) with the exclusion of dummies for speciality and healthcare institutions. In addition, segregation variables are included: $Fem.Spec_g$ corresponds to the percentage of positions held by women in the speciality g, and $Fem.Inst_g$ to the percentage of women in the institution n, the two covariates associated with labour market feminisation.

With the estimated coefficients of equation (2), Bayard et al. (2003) construct the following labour income decomposition between women and men:

$$\begin{aligned} ln(y_f) - ln(y_m) = \hat{\beta} &+ (Fem.Spec_f - Fem.Spec_m)\,\hat{\gamma} + (Fem.Ins_f - Fem.Ins_m)\,\hat{\delta} \\ &+ (X_f - X_m)'\,\hat{\Lambda} \end{aligned} \tag{3}$$

[3] To obtain the raw gender gap, we just regress the dependent variable on the female indicator.

Where the subscripts f and m on the variables indicate the means for women and men, respectively. The decomposition shows how much of the labour income gap is explained by the segregation of women into particular specialities or institutions $((Fem.Spec_f - Fem.Spec_m)\hat{\gamma})$ and $((Fem.Ins_f - Fem.Ins_m)\hat{\delta})$; by differences in observable individual characteristics $((X_f - X_m)'\hat{\Lambda})$; and by gender differences in wages controlling for segregation and the other characteristics $(\hat{\beta})$. While the terms associated with mean differences in segregation and other observable controls can be viewed as a *between* effect, the $\hat{\beta}$ coefficient implicitly represents the gender pay gap *within* covariates cells. Given that $Fem.Spec_f$ and $Fem.Spec_m$ represents the average proportion of females in female and male occupations respectively, if women are segregated, the average for women will be higher than for men, and $Fem.Spec_f - Fem.Spec_m > 0$. The contribution of healthcare institutions is interpreted similarly.

This decomposition can be viewed as an Oaxaca (1973) and Blinder (1973) decomposition (OB) that imposes the same coefficients for males and females. We also perform the OB decomposition without this assumption; a more flexible approach that consists of estimating regressions for females and males separately and computing the decomposition as follows:[4]

$$\begin{aligned} ln(y_f) - ln(y_m) &= \hat{\Delta}^{\mu}_{O} \\ &= \Big[(Fem.Spec_f - Fem.Spec_m)\,\hat{\gamma}_m + (Fem.Ins_f - Fem.Ins_m)\,\hat{\delta}_m \\ &+ (X_f - X_m)'\,\hat{\Lambda}_m\Big] \\ &+ \Big[Fem.Spec_f(\hat{\gamma}_f - \hat{\gamma}_m) + Fem.Ins_f(\hat{\delta}_f - \hat{\delta}_m) + X_f'\left(\hat{\Lambda}_f - \hat{\Lambda}_m\right)\Big] \\ &= \hat{\Delta}^{\mu}_{X} + \hat{\Delta}^{\mu}_{S} \end{aligned} \tag{4}$$

The last term in equation (4) links the expression for the decomposition in our particular case to a more general OB-type decomposition, as in Fortin et al. (2011). The term $\hat{\Delta}^{\mu}_{X}$ is the *composition effect*, also called the “quantity effect” or the “explained” (by group differences) part of the decomposition. The term $\hat{\Delta}^{\mu}_{S}$ is the *labour income structure effect*, also called the “unexplained” part of the labour income gap or the portion due to discrimination. As Jann (2008) points out, the unexplained part can also capture the potential effects of differences in unobserved characteristics.

Equation (4) is formulated taking the male coefficients as the reference labour income structure. This means, for example, that the explained effect compares men’s actual mean outcome

[4] This decomposition is also called a “two-fold” decomposition since it divides the contribution to the mean difference essentially into two components. However, there are other ways to compute this difference. For a comprehensive presentation and further details of the method, its possible extensions, and limitations, see for example Jann (2008) and section 3 of Firpo et al. (2018).

with men's counterfactual mean outcome if they had women's covariates ($X_f' B_m - X_m' B_m$).[5] From another point of view, the male coefficients (the male labour income structure) are considered as the nondiscriminatory coefficients, i.e., discrimination is assumed to occur directly against women. However, the male labour income structure does not necessarily represent the appropriate returns that women would be paid if labour market discrimination did not exist. Many alternative choices of counterfactuals have been proposed to achieve this kind of issue, based on different elections of the nondiscriminatory coefficients (Jann, 2008). A simple two-fold approach is adopted here to maintain the coherence of presentation and comparability with Bayard's decomposition.

Equation (4) provides a detailed decomposition that considers the contribution of individual or groups of covariates to the mean difference in the outcome, given the linear additive assumption of the Oaxaca-Blinder approach. In the context of this study, a detailed decomposition can help us answer questions such as: what proportion of the overall gender gap is due to the gender composition of each speciality or group of specialities, and to what extent does the relative return to specialities (or groups of specialities) explain the gender pay gap. To perform this detailed decomposition, we regress physician specialities as explanatory variables separately for women and men, as in equation (1), and compute the detailed decomposition based on these regressions. For clarity, we perform the detailed decomposition by grouping specialities according to the definition presented in Table 2.

Since the speciality group is a categorical variable, two problems arise when performing an OB decomposition. First, since no absolute interpretation is possible (i.e., there is no natural zero), a reference category must be arbitrarily chosen.[6] The common practice varies depending on the specific context, but it is usual to omit the reference category for the remaining categories in the distribution. The problem here is that, in the explained effect, the coefficient at which the difference in the mean of the variables is "priced"may differ significantly depending on the omitted category and the relative payment structure. This can lead to very different detailed effects depending on the case, although the total group structure effect is not affected.

The second problem concerns the unexplained effect and stems from the fact that the intercept of the detailed decomposition includes the difference in coefficients between groups for the omitted category. Consequently, the effect of the group structure will vary depending on

[5] Similarly, the unexplained part of the decomposition $X_f' B_f - X_f' B_m$ compares female's actual mean outcome with those they would have if they were paid at male's prices.

[6] The necessary omission of one of the categories in the regression implies that the coefficients must always be interpreted with respect to the omitted category. For example, in the medical speciality case, if General Medicine is omitted, then the coefficient associated with, e.g., Paediatric, represents the difference in payment between those specialities.

the omitted category. Different alternatives have been proposed to address this problem, based on normalizing the coefficients so that the choice of the omitted category is irrelevant. In this paper, we adopt the normalization proposed by Fortin et al. (2011).

3.2.3 Vertical segregation

Third, to account for the existence of vertical segregation (i.e different gender gaps along the income distribution), we estimate re-centered influence function (RIF) regressions for quantiles, proposed by Firpo et al. (2009). This approach allows us to estimate the partial effects of the covariates on the unconditional quantile of the variable.[7] The method consists of running a regression of a particular transformation of the dependent variable -the RIF of the unconditional quantile- on the covariates. As a result, as many coefficients as quantiles are estimated for each covariate. In particular, if the gender coefficient is larger in the higher quantiles of the wage distribution, then it is possible to infer that the barriers faced by women are greater for higher labour incomes. This can be interpreted as evidence in favour of the existence of a glass ceiling.

The first step of the method consists of estimating the RIF. Consider a statistic v associated with the distribution of the outcome y, $v(F_y)$, and let $IF(y;v)$ be the associated influence function, defined as the robustness measure of v to the presence of outliers. Define $RIF(y;v) = v(F_y) + IF(y;v)$. As can be seen in Firpo et al. (2009), in the case of the quantile τ of y,$v = Q_\tau$, the above expression for the RIF is defined as:

$$RIF(y;Q_\tau) = Q_\tau + \frac{\tau - \mathbb{I}\{y < Q_\tau\}}{f_y(Q_\tau)} \tag{5}$$

Where $\mathbb{I}\{\cdot\}$ is the indicator function and f_y the pdf of y. Q_τ is computed directly of the sample and $f_y(Q_\tau)$ is estimated using kernel's methods.

Once the $RIF(y;Q_\tau$ has been estimated for each observation, the second step consists of running a regression of this variable on the explanatory variables. To see why, using the fact that $\mathbb{I}\{y < Q_\tau\} = 1 - \mathbb{I}\{y \geq Q_\tau\}$, equation (5) can be writing as:

$$RIF(y;Q_\tau) = Q_\tau + \frac{\tau - 1}{f_y(Q_\tau)} + \frac{\mathbb{I}\{y \geq Q_\tau\}}{f_y(Q_\tau)} = c_{1,\tau}\mathbb{I}\{y \geq Q_\tau\} + c_{2,\tau} \tag{6}$$

Where $c_{1,\tau} = 1/f_y(Q_\tau)$ and $c_{2,\tau} = Q_\tau + (\tau - 1)/f_y(Q_\tau)$. Taking expectations and conditioning on covariates X:

$$\mathbb{E}\left[RIF(y;Q_\tau)\right] = c_{1,\tau}Pr[y \geq Q_\tau | X = x] + c_{2,\tau} \tag{7}$$

Thus, the model to the expected RIF implies estimating a probability model of y conditional on the covariates X. Firpo et al. (2009) propose three alternatives to do this (LPM, Logit, and

[7]This is why it is also often referred to as the Unconditional Quantile Regression (UQR) method.

Non-parametric estimator). In the case of assuming a linear probability model, $\mathbb{I}\{y \geq Q_\tau\} = x'\beta + \mu$, and under the conditional independence assumption $\mathbb{E}[\mu|x] = 0$, we have:

$$RIF(y; Q_\tau) = c_{1,\tau}\left(x'\beta + \mu\right) + c_{2,\tau} = c_{2,\tau} + x'\beta^* + \mu^* \tag{8}$$

The authors refer to this alternative as the RIF-OLS estimation method. A potential issue of the method is that the linearity assumption in the LPM could mislead nonlinear relationships, and thus bias the estimates. In the case of binary explanatory variables (such as gender), an additional problem arises in the estimates of partial effects. They must be interpreted carefully since RIFs are locally linear approximations of such effects and in the case of large discrete changes the estimates may be subject to relevant biases (Rios-Avila, 2020).

On the other hand, in addition to its relative computational efficiency, the RIF-regression method provides a simple and direct way to estimate partial effects. Another advantage of this method is that could be directly introduced in the OB framework, and thus compute aggregated and detailed decomposition for the different points of the distribution. Following Fortin et al. (2011), letting $\hat{\Gamma}_{g,t}$ the estimated coefficients of the unconditional quantile regression for each group (females and males in our case), an equivalent of the OB decomposition for any unconditional quantile τ is:

$$\widehat{\Delta}_O^\tau = \left(X_f - X_m\right)' \widehat{\Gamma}_{m,\tau} + X_f'(\widehat{\Gamma}_{f,\tau} - \widehat{\Gamma}_{m,\tau}) = \widehat{\Delta}_X^\tau + \widehat{\Delta}_S^\tau \tag{9}$$

The composition or explained effect (Δ_X^τ) can be rewritten in terms of the contribution of each covariate:

$$\widehat{\Delta}_X^\tau = \sum_{k=1}^{K} (X_{fk} - X_{mk})' \widehat{\Gamma}_{mk,\tau} \tag{10}$$

And the detailed wage structure or unexplained effect is:[8]

$$\widehat{\Delta}_S^\tau = \sum_{k=1}^{K} X_{fk}' (\widehat{\Gamma} fk, \tau - \widehat{\Gamma} mk, \tau) \tag{11}$$

The linear specification may not be valid for significant changes in the covariates, potentially leading to bias, as previously mentioned. To address this issue, Fortin et al. (2011) suggests a solution that incorporates a combination of reweighting and RIF-regression methods, which is the approach adopted in this study. The idea is to apply a weighting function that corrects for potential misspecification, generating a counterfactual that makes the distributions of covariates similar between groups. The reweighting function is:

$$w(X) = \frac{P(\text{female} \mid X)}{P(\text{female})} \frac{P(\text{male})}{P(\text{male} \mid X)} \tag{12}$$

[8]As in the case of the mean, the unexplained effect may be subject to the omitted group problem mentioned above.

Next, estimate the RIF-regression using the reweighted covariates to obtain the coefficients necessary for computing the decomposition, which is similar to the one presented in equations (9), (10), and (11). However, it's important to note that the reweighting process results in a slightly different version of the explained and unexplained effects. This is because the counterfactual now involves a reweighted version of the reference group. As shown by Fortin et al. (2011), it is possible to express the explained and unexplained effects as follows:

$$
\begin{aligned}
\widehat{\Delta}_X^{\tau} &= \underbrace{(X_m^C - X_m)'\widehat{\Gamma}_{m,\tau}}_{\Delta_{X,p}^{\tau}} + \underbrace{X_m^C(\widehat{\Gamma}m,\tau^C - \widehat{\Gamma}m,\tau)}_{\Delta_{X,e}^{\tau}} \\
\widehat{\Delta}_S^{\tau} &= \underbrace{X_f'(\widehat{\Gamma}f,\tau - \widehat{\Gamma}m,\tau^C)}_{\Delta_{S,p}^{\tau}} + \underbrace{(X_f - X_m^C)'\widehat{\Gamma}m,\tau^C}_{\Delta_{S,e}^{\tau}}
\end{aligned}
\tag{13}
$$

Where the counterfactual components (those with superscript C) came from the reweighted RIF-regression described before. The terms $\widehat{\Delta}_{X,p}^{\tau}$ and $\widehat{\Delta}_{S,p}^{\tau}$ correspond to the "pure.$^{\text{ex}}$plained and unexplained effect, respectively. $\widehat{\Delta}_{X,e}^{\tau}$, called the *total specification error*, corresponds to the difference between the total labour income structure across the classic OB and the reweighted-regression decomposition. It is a linear projection error associated with the fact that the RIF regression-based procedure only provides a first-order approximation to the composition effect. Hence, the magnitude of this error provides a specification test of the procedure. On the other hand, $\widehat{\Delta}_{S,e}^{\tau}$ is the *total reweighting error* and represents the difference between the total explained component across the two decompositions.

4 Results

4.1 Gender pay gap

In this subsection, we present an analysis based on OLS estimates with pooled data from 2008 to 2018 (Table 4). The results show that, on average, women physicians earn less money than men by position in the private sector: the raw gaps are estimated at -30 % in monthly income and -16 % for hourly income. When controls are included in the models, although the gap is reduced, it remains negative and significant: conditional differences are -9 % for monthly income and -6 % for hourly income. Therefore, we find first evidence of a pay penalty against women in the healthcare sector.

Then, we present estimates of the gross gap and the conditional gap of the logarithm of medical earnings by gender by year (table A.1. On average, female positions have lower earnings:

Cuadro 4: Raw and conditional gender gaps - average 2008-2018

	Log Ingreso Mensual		Log Ingreso Horario	
	Sin controles	Con controles	Sin controles	Con controles
Female	-0,2995***	-0.0950***	-0.1623***	-0.0583***
Age		0.0455***		0.0347***
Age2		-0.0003***		-0.0002***
Hours		0.0049***		
Surgical act		0.0272***		
Non surgical act		0.0003***		0.0000*
CAD		0.6592***		0.1292***
Specialty		Yes		Yes
Institution		Yes		Yes
Rel. Inst		Yes		Yes
Year		Yes		Yes
Cons	11.13***	9.4001***	7,331***	6.1690***

N=525,896. OLS estimations with pooled data from 2008 to 2018. Robust standard errors.
$^{*}p < 0{,}1$, $^{**}p < 0{,}05$, $^{***}p < 0{,}01$
Source: SCARH.

the gross gap of the logarithm of monthly earnings stood at -27 % in 2018, a smaller difference than the 2008 estimate of -34 %. The improvement is due in part to the fact that male physicians decreased the average number of hours worked and acts performed during the period. The hours worked by female physicians also decreased, although less than those of male physicians. These results can be seen in Tables A.6 and A.7 in Appendix. The difference in gross hourly earnings stood at -16 % in 2018. The difference is smaller than in the monthly case for the same year, in part due to women working fewer hours than men, as shown by Colacce et al. (2020) for the rest of the female workers. In terms of its temporal evolution, we observe only a slight reduction compared to the value in 2008.

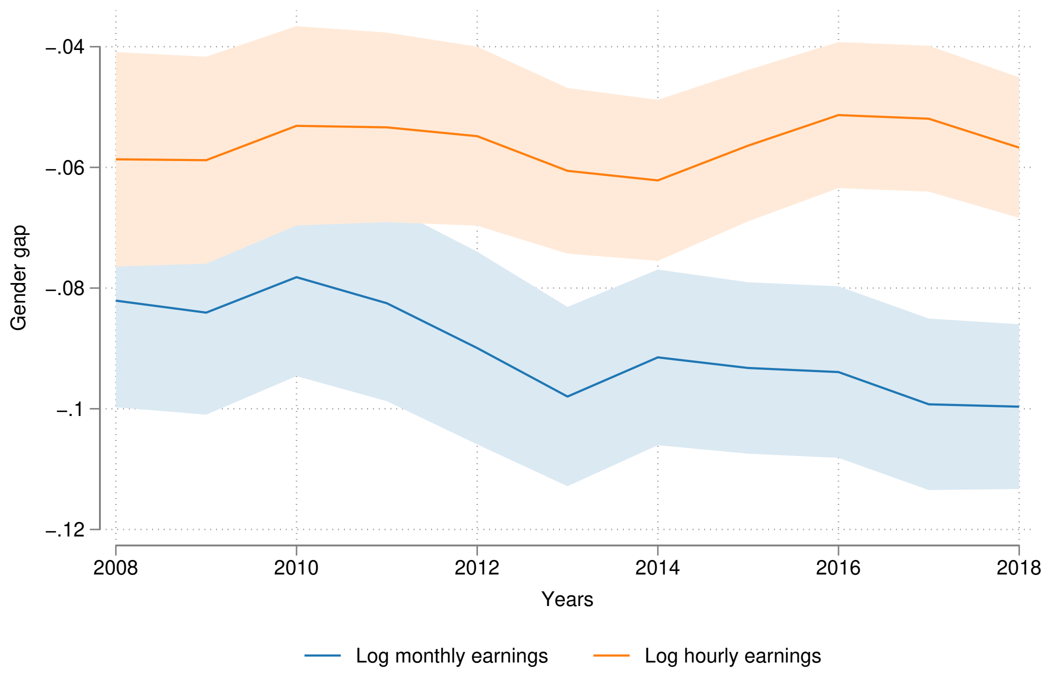
Figure 4 presents the coefficient estimates associated with the variable $Female$ in equation 1, an OLS estimation with monthly earnings and hourly earnings as the dependent variable, controlling for individual and occupation characteristics (the regression results can be seen in Table A.8 and A.9). The conditional gap is smaller than the raw gap, but the coefficient remains negative and significant at 1 %. This indicates that men have higher earnings than women and that this difference is not explained by any other covariate included in the model. For monthly earnings, the estimate of the conditional gap was -9.9 % in 2018. To interpret this coefficient as a semi-elasticity, the transformation $exp(\beta 2) - 1$ is performed. It is concluded that in 2018 female physician positions received on average 9.4 % lower monthly income than male physician positions, controlling for individual and position characteristics. In the model with controls, the coefficient associated with the variable $Female$ shows a slight increase between 2008 and 2018.

When we look at hourly earnings, the coefficient of the binary variable $Female$ is also negative, but it is lower than the one estimated for monthly payments. In 2018, female physicians, on average, received an hourly income 6 % lower than their male counterparts in similar positions with similar characteristics. This figure closely mirrors the estimate from 2008, indicating that the conditional hourly income gap has remained relatively stable over the ten years under analysis

The estimated hourly earnings gap for physicians is significantly smaller than the one reported by Espino et al. (2014) or the entire labor force, which was -25 % in 2011. The difference in earnings attributed to the gender of the individual for medical positions also turned out to be smaller than the estimate of Espino et al. (2014) for workers with tertiary education, which is -14 % in 2011. The authors argue that the variation in the coefficients when comparing total wage earners with the most educated individuals, can be attributed to the presence of objective forms of certification for specific skills and knowledge among tertiary-educated wage earners. These certifications are typically required at the time of hiring and serve as the basis for determining wages. This same observation can be applied to physicians, who are among the most highly educated within the category of tertiary-educated workers.

The difference in hourly labor income between male and female physicians is also smaller than the one found by Colacce et al. (2020) for all workers in 2018. The authors estimate that on average women earned 19 % less than men with the same characteristics. However, Colacce et al. (2020) finds a similar gap result for formal workers, which is around -5 % in 2018. Finally, our results are similar to those found for Magnusson (2016) for Swedish physicians.

Figura 4: Conditional gender pay gap



Note: The lines report coefficients of the binary variable Female in an OLS regression, with their confidence intervals (shadows, robust standard errors). The specifications include controls by age, age squared, hours, surgical and non-surgical acts, dummy indicating CAD position, dummy indicating whether the worker is permanent, substitute or independent, fixed effects by speciality, and fixed effects by the healthcare institution. **Source**: SCARH.

4.2 Horizontal segregation

4.2.1 Measuring horizontal segregation

We calculate segregation indices only for hourly earnings, as our analysis focused on positions rather than the sum of individual incomes. Monthly comparisons may not be entirely accurate for our purposes. To examine the presence of horizontal segregation, we compute the Duncan (DI) and Karmel and Maclachlan (KM) segregation indices for each year (see Table A.10). Additionally, we conducted a decomposition of the change in DI between 2008 and 2018 (see Table A.11)

Our analysis shows a reduction in the DI for medical specialities in the IAMCs over this period, declining from 32 % in 2008 to 28 % in 2018, representing an 11 % decrease. These results align with studies of occupational segregation in Uruguay, which report lower levels of segregation among highly qualified occupations (Katzkowicz et al., 2013). For instance, Katzkowicz et al. (2013) report a DI value of 28 % for skilled workers out of the total employed in 2011, which is significantly lower than the value calculated for less skilled workers (DI of 58 %). Similarly, Espino (2013) found a DI value of 61 % for all salaried workers in Uruguay in 2010, whereas Espino et al. (2014) calculated a DI of 62 % for all salaried employees in 2011, and of 37 % for those with more than 12 years of education. The changes in the DI over time are driven by two main factors: the occupational structure of the labour force (Occupational effect) and the gender composition within occupations (Gender effect). Our decomposition analysis reveals that the variation in the DI between 2008 and 2018 is mainly driven by the Gender effect, which accounts for 57 % of the total change, followed by the Occupational effect, which explains 25 %. The residual component explains the remaining 25 % of the variation (see Table A.11). Similarly, the KM index indicates that in 2018, 14 % of medical positions would need to change speciality for the distribution of men and women by speciality to be equalised (see Table A.10). This represents a 12 % decrease from the 2008 KM value, which is slightly larger than the drop observed in the ID. This disparity is attributable to the rise in female representation in the overall number of positions from 48 % to 57 %.

We examine the influence of horizontal segregation on the physician income labour gap and present the results in Table 5. We used OLS regression models with segregation variables for the years 2008 and 2018, controlling for speciality and institution by including the percentage of women in each as an explanatory variable. This allows us to capture the effect of working in an environment with a higher proportion of women on payments. The coefficient on the *Female* variable estimate with segregation controls in 2018 was slightly lower than in the previous model (in absolute value).

The results of the estimations incorporating the segregation variables for all years are presented in Table A.12. Comparing the magnitude of the coefficient with the estimates for the branch segregation coefficient of Espino et al. (2014), they are closer to those estimated for the total employed than for workers with tertiary education. This means that horizontal segregation could be more important in explaining the labour income gap in the medical sector than for other workers with tertiary education. Regarding the influence of female participation by institutions on income, the estimated parameters show a positive sign for most years.

Cuadro 5: The influence of horizontal segregation in the gender pay gap, 2008 and 2018

	2008 Log. of hourly income with seg	2018 Log. of hourly income with seg
Female	-0.0573***	-0.0500***
Age	0.0534***	0.0522***
Age2	-0.0004***	-0.0004***
Non-surgical Act	-0.0000**	0.0007***
CAD	No	-0.0512***
% Woman by specialty	-0.3199***	-0.4722***
% Woman by institution	0.8838***	1.0111***
Montevideo	-0.0699***	0.0894***
Specialty	No	No
Institution	No	No
Rel. Inst	Yes	Yes
Cons	5.3255***	5.4960**

Notes: Robust standard errors.
The dependent variable is the logarithm of the hourly wage
and the controls are those specified in Equation 2.
$^{*}p < 0{,}1$, $^{**}p < 0{,}05$, $^{***}p < 0{,}01$
Source: SCARH.

4.2.2 Decomposing gross gaps

Table 6 presents the results of the decomposition of the differences between the logarithms of women's and men's labour income from the models that include the segregation variables in 2018. Additionally, you can find detailed information about the contribution of each variable for all years in Table A.13 in the Appendix. This decomposition allows us to break down the gross labour income gap by assessing the contribution of each covariate, following the approach proposed by Bayard et al. (2003). As expected, the *Female* variable makes a significant contribution to the hourly labour income gap. The contribution of the gender variable to hourly labour income decreased slightly, from 34 % to 32 % between 2008 and 2018. This trend aligns with the evolution of the coefficients estimated in the models that do not include the segregation variables. *Age* also explains a significant proportion of the gap. The age distribution of women is younger than that of men. As age approximates work experience, it is positively correlated with income and this contributes to men earning more. This point is significant to consider because, over time, as women age, a substantial portion of the income gap could potentially decrease. However, it's essential to account for the possibility that women might retire from the labour market earlier than men, which could offset some of this transition.

The concentration of women in specific specialties is the most significant component of the gross gap. This component also exhibits a growing trend over time, increasing from 33 % in 2008 to 47 % in 2018. This finding implies that horizontal segregation is gaining importance in explaining gender differences in labour earnings.

The results indicate that women in IAMCs hold positions with lower incomes compared to men. The concentration of women in specific specialties plays a significant role in explaining these differences. Nonetheless, there remains an unexplained component that cannot be accounted for by this variable or any of the other variables included in the models.

Cuadro 6: Decomposition of labour income gap by gender, 2018

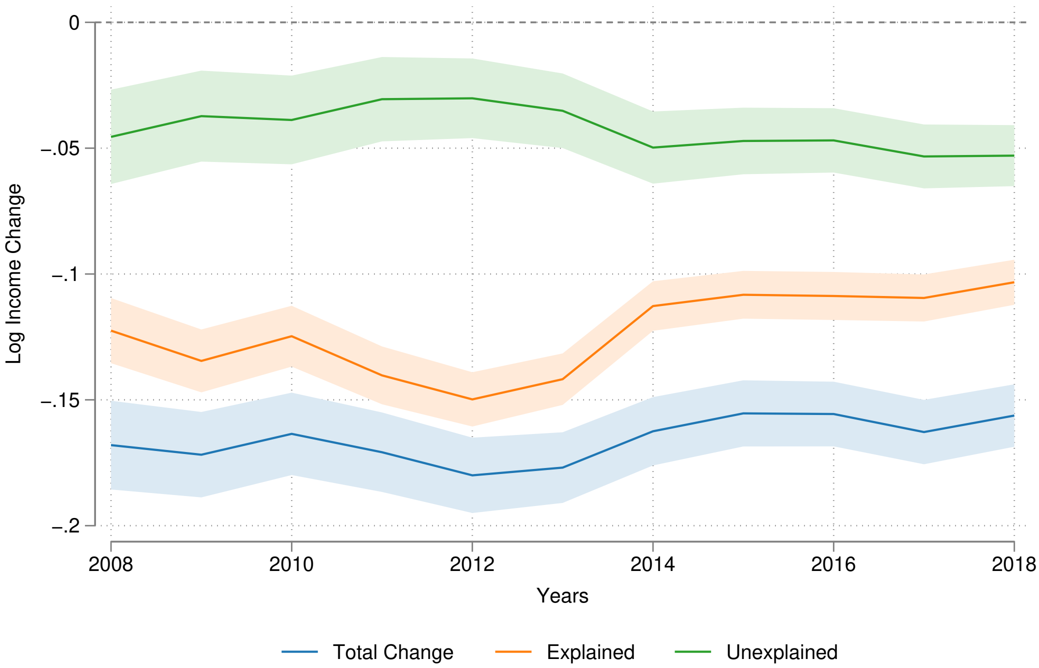
	Women	Men	Difference	Absolute contribution	Relative contribution
Log. hourly income	7.22	7.38	-0.16		
Female	1	0	1	-0.05	32 %
Age	45	48	-3	-0.17	111 %
Age sq	2142	2474	-332	0.14	-91 %
Nin-surgical act	67	70	-3	0.00	1 %
CAD	0.07	0.05	0.06	0.00	0 %
% Woman by specialty.	0.63	0.48	0.15	-0.07	47 %
% Woman by institution	0.57	0.56	0.01	0.01	-6 %
Montevideo	0.67	0.65	0.02	0.00	-1 %
Substitutes	0.22	0.18	0.04	0.00	3 %
Permanent Substitutes	0.22	0.18	0.04	0.00	3 %
Self-employed	0.12	0.14	-0.02	0.00	2 %

Notes: Decomposition according to Bayard et al. (2003) and Equation 3.
Source: SCARH.

Subsequently, we conducted separate regressions for males and females to perform an Oaxaca-Blinder decomposition (see Table A.14). Segregation by speciality is one of the most influential variables in explaining the gap. This implies that horizontal segregation indeed plays a role in gender disparities in labour income. Nevertheless, a portion of the gap remains unexplained.

Finally, Figure 5 and Table A.15 in the Appendix provide the results for an alternative decomposition that takes into account the impact of medical specialties on the gender gap. The decomposition reveals the same patterns discussed earlier, with the explained effect being the driving force behind the evolution of the gender gap. However, as shown in the *AS* row in the explained part of Table A.15, specialties related to Anesthetic and Surgical Specialties play a central role in the composition effect. Furthermore, the influence of these medical specialties increases towards the end of the period. This aligns with previous findings and confirms that certain areas of medicine historically reserved for men continue to have a significant impact.

Figura 5: Decomposition of gender pay gap including groups of medical specialities, 2008 to 2018



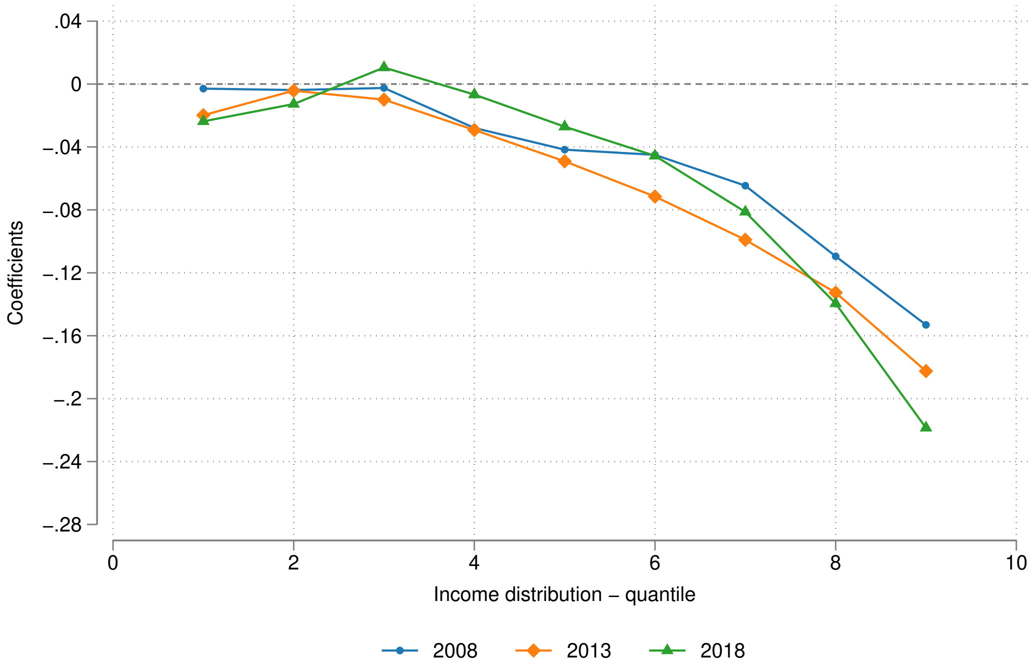
Note: The lines report the raw differences between female and male average labour income for each year (Total Change), and the estimates of aggregate decomposition in the explained part (change in the average characteristics) and unexplained part (change due to differences in returns to those characteristics). Confidence intervals in shadow areas. The dependent variable is the log of hourly labour income, and explanatory variables include age, age squared, non-surgical acts, dummies indicating CAD position, whether the worker is permanent, substitute, or independent, and fixed effects by specialities and healthcare institutions. **Source**: SCARH.

4.3 Vertical segregation

The previous results show that there is a gender-based income disparity, and it could be attributed to individuals' gender. These results were calculated based on average labour incomes. Now, we aim to explore differences across the distribution and test the 'glass ceiling' hypothesis. To achieve this, we employ unconditional quantile regressions, proposed by Firpo et al. (2009).

Figure 6 suggests the existence of a gender pay gap throughout the entire distribution. The estimated coefficients at the different points of the labour income distribution are negative in all years considered (2008, 2013, and 2018), with the only exception of 3rd quantil in 2018. All coefficients are significant above the median. However, higher coefficients are observed in the right tail of the distribution. This means that the pay gender gap widens for higher labour incomes; evidence of the presence of a glass ceiling (Table A.16 in the Appendix presents the estimation of unconditional quantile regressions for selected years).

Figura 6: Unconditional quantile regression coefficients (selected years)

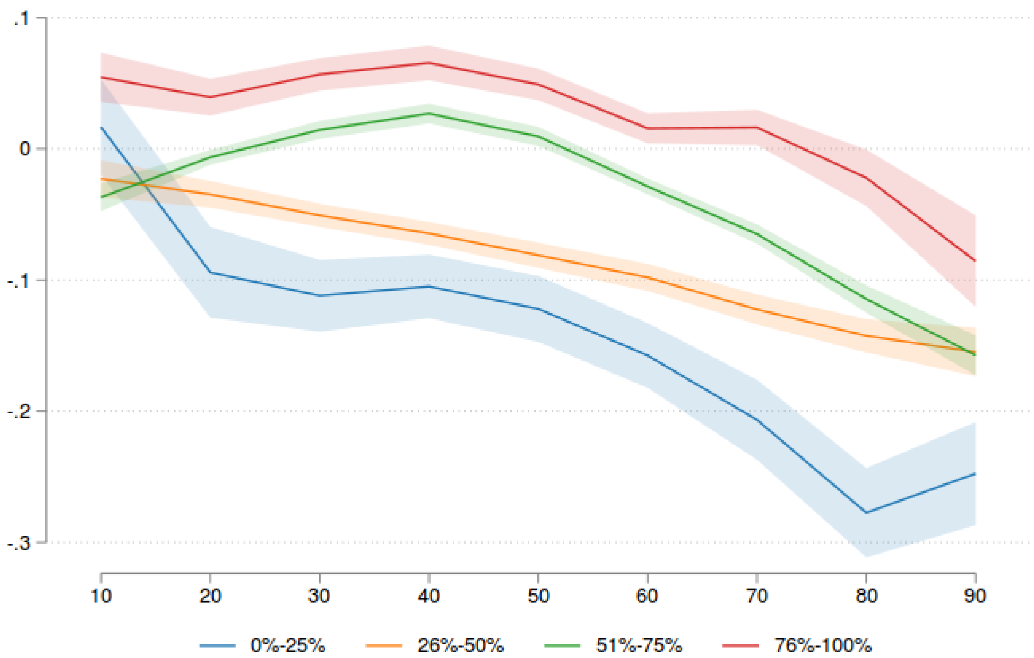


Note: The lines show the labour income gender gap for different quantiles and years. The RIF specifications include controls by age, age squared, non-surgical acts, dummy indicating CAD position, dummy indicating whether the worker is permanent, substitute or independent, and fixed effects by speciality and healthcare institution. **Source**: SCARH.

The results of the reweighted RIF decomposition presented in Tables A.17 and A.18 reinforce the previous statements and show some interesting features. First, the average gap could not be quite precise to describe gender pay differences. The total difference is much longer at percentile 90 than the median and bottom of the distribution. Second, while the explained effects have a more relevant impact at the bottom and middle of the labour income distribution, both the explained and unexplained effects play a similar role at the top of incomes. In summary, these findings align with the presence of a significant glass-ceiling effect for female physicians.

Then, in order to account for heterogeneous differences, we consider different groups of specialties and analyse the gender pay gap along the labour income distribution for each group. This analysis offers a more comprehensive understanding of the factors contributing to the glass ceiling effect among female physicians. Initially, we categorised specialties based on the percentage of female representation, resulting in four distinct groups: 0 to 25 % of women, 25 to 50 % of women, 50 to 75 % of women, and 75 % of women or more. The results indicate a significant decline in female coefficients at the upper levels of the labour income distribution across all category groups (Figure 7). This observation emphasizes the presence of the glass ceiling phenomenon, even within specialties dominated by women. However, the disparity is most pronounced in specialties where female representation is at 25 % or less.

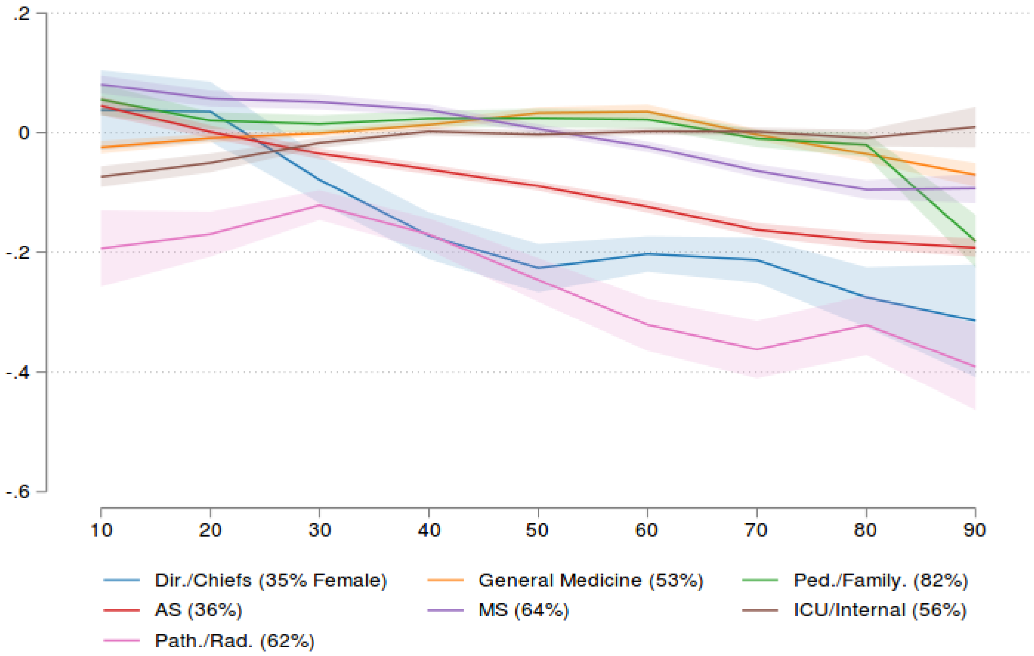
Figura 7: Unconditional quantile regression coefficients by specialty female participation



Note: The lines report coefficients of the binary variable Female in an RIF regression of log hourly labour income for each group with pooled data from 2008 to 2018, with their confidence intervals (shadows, bootstrapped standard errors with 500 replication of the entire procedure). The specifications include controls by age, age squared, non-surgical acts, dummy indicating CAD position, dummy indicating whether the worker is permanent, substitute or independent, fixed effects by speciality, healthcare institution, and year. Groups were formed by female participation of the specialty. **Source**: SCARH.

Figure 8 replicates the same exercise but considers seven specialty groups, which were categorized based on the type of medical practice. These results reveal distinct patterns within each group. Firstly, anesthesiologists and surgeons, along with directors and chiefs, emerge as significant contributors to both the income gap and the glass ceiling effect. In these cases, there are substantial reductions in the coefficients across the income distribution. Additionally, there is a substantial disparity evident for pathologists and radiologists, marked by a significant decline in coefficients. Medical specialists (MS) also exhibit evidence of a glass ceiling phenomenon, but less dramatic. A different image emerges for general practitioners, pediatricians, and family medicine practitioners, where the pay gender gap is less pronounced but the glass ceiling is still observed over the 80th percentile. Finally, it is interesting the result observed within the group comprising ICU (Intensive Care Unit) physicians, internal medicine specialists, and neonatologists. Although the gap is relatively small, is the only group in which there is an increase in coefficients across the labour income distribution.

Figura 8: Unconditional quantile regression coefficients by specialty group.



Note: The lines report coefficients of the binary variable Female in an RIF regression of log hourly income for each group with pooled data from 2008 to 2018, with their confidence intervals (shadows, bootstrapped standard errors with 500 replication of the entire procedure). The specifications include controls by age, age squared, non-surgical acts, dummy indicating CAD position, dummy indicating whether the worker is permanent, substitute or independent, fixed effects by speciality, healthcare institution, and year. The legend includes the average proportion of women in the period within each category. The specialty groups were formed according to the modality of work. Details of the specialty groups are shown in A.2. MS = Medical Specialties; AS = Anesthetic and Surgical Specialties. **Source**: SCARH.

We observe that the groups with less or no pay gender gap have in common their mode of practice and substitutability between professionals. These types of specialties used to have more presential hours in the hospital and shared patients. These phenomena could be the reason for the reduction in the pay gender gap. Following Goldin (2014), greater substitutability between workers would produce fewer gender pay gaps.

5 Conclusions

In this paper, we study the labour income gap between male and female physicians in Uruguay and the role of segregation in this gap. Through the use of OLS models, we found that there is a gender pay gap among physicians, even after controlling for observable position characteristics, such as medical speciality. This suggests that the remaining difference in earnings is associated with a discriminatory factor. Specifically, in 2018, women in IAMCs had on average 6 % lower hourly earnings than men, considering personal and position characteristics. The conditional gap is lower than what has been reported in previous studies for the overall Uruguayan workforce Espino et al. (2014); Colacce et al. (2020), but remains stable between 2008 and 2018.

We also aimed to determine whether there is horizontal segregation by specialty. Our findings indicate the presence of segregation, as measured by Duncan's and Karmel and Maclachlan's indices. In 2018, it was found that 28 % of women would need to change specialties to achieve gender equality in distribution. There was a decrease in the segregation index during the period under analysis, which is primarily attributed to a change in the gender composition of occupations (50 %) and, to a lesser extent, changes in the occupational structure (25 %).

Additionally, we estimate regressions and decompositions of the gap following the methodology of Bayard et al. (2003). The decomposition of the hourly earnings gap shows that segregation by speciality is the variable with the largest contribution, explaining 47 % of the 2018 hourly earnings gap. This percentage showed an increase between 2008 and 2018. The component associated with the gender of the individual explains 32 % of the difference. Moreover, decompositions were performed with estimates from sex-separated regressions. In this case, it was also observed that speciality segregation is the variable with the greatest influence on the labour income gap.

Next, we sought to answer whether female physicians face a glass ceiling, which does not allow them to reach the highest salaries. We analysed differences in salary income beyond the mean, due to the estimation of quantitative regressions using the RIF method (Firpo et al., 2009). The results show evidence consistent with the presence of a glass ceiling, since the estimated conditional gap increases in the right tail of the income distribution. Furthermore, the estimate in the 90th quantile shows an increase between 2008 and 2018, indicating that in that period, the difficulties for female physicians to access higher-paying jobs increased. This suggests that the barriers for women to advance in their careers are contributing to the gender income gap in the healthcare sector in Uruguay. We also find that the presence of a glass ceiling is still notable in medical specialties with a majority of women. However, the disparity is more pronounced in specialties dominated by men. Moreover, the analysis of gender pay beyond the mean has also revealed intriguing results within specific specialty groups. Notably, anesthesiologists, surgeons, and directors in surgical specialties exhibit the most substantial discrepancies in pay, especially for higher income. In contrast, there appears to be no discernible glass ceiling or gender wage gap among professionals in the ICU, internal medicine, and neonatology fields.

These findings provide valuable information to policymakers, highlighting the need to generate strategies to reduce gender inequality among workers. Further research on the determinants of these differences is crucial to advance the implementation of tools to reduce them. This is especially significant because labour income is the main source of income for the majority of the population. The lower income earned by women reduces their capacity to consume and make decisions about household expenditure. Consequently, this reduces their ability to manage independently.

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APPENDIX

A Appendix: Tables and Figures

Cuadro A.1: Quotas for residencies and traditional postgraduate programs in 2015

Specialty	Residencies Quotas	Postgraduate Quotas
Health Services Administration	5	-
Pathological Anatomy	3	7
Anesthesiology	15	-
Cardiology	9	22
General Surgery	13	-
Plastic Surgery	3	-
Vascular Surgery	1	-
Dermatology	4	8
Endocrinology	1	8
Epidemiology	1	-
Physiatry	4	-
Gastroenterology	2	10
Geriatrics	4	13
Gynecotocology	26	-
Hematology	2	No Limit
Imaging	10	14
Infectology	1	-
Clinical Laboratory	4	15
Family and Community Medicine	29	No Limit
Intensive Care Medicine	23	40
Internal Medicine	39	No Limit
Legal Medicine	1	6
Nuclear Medicine	1	6
Transfusion Medicine	1	10
Microbiology	1	8
Nephrology	5	15
Pneumology	1	10
Neurology	5	6
Ophthalmology	6	10
Medical Oncology	4	10
Radiation Oncology	2	6
Otorhinolaryngology	2	6
Parasitology	1	No Limit
Pediatrics	42	40
Psychiatry	4	No Limit
Rheumatology	1	10
Occupational Health	1	No Limit
Toxicology	3	No Limit
Traumatology	8	-
Urology	6	-
Total	294	-

Source: Contreras and Faggetti (2016)

Cuadro A.2: Specialty Groups

Specialty Group	**Specialty**
Directors and Chiefs	General Direction Sanatorium Direction Technical Direction Department Heads and/or Team Leaders Other Departmental Responsibilities
General Medicine	General Medicine
Pediatrics and Family Medicine	Family Medicine Pediatrics
Surgical Anesthetic (AQ)	Anesthesiology Vascular Surgery Other Surgical Anesthetic Physicians Surgery Neurosurgery Surgical Assistants Pediatric Surgery Gynecology and Obstetrics Traumatology-Orthopedics Plastic and Reconstructive Surgery Ophthalmology Urology Thoracic Surgery Otorhinolaryngology
Medical Specialties (MS)	Cardiology Hematology Pneumology Emergency Medicine Dermatology Infectious Diseases Neurology Geriatrics-Gerontology Endocrinology Physiotherapy Physician Neuropediatrics Other Medical Specialties Physical Medicine and Rehabilitation Hemotherapy Physician Oncology Other Non-Surgical Anesthetic Physicians Gastroenterology Nephrology Allergology Rheumatology Psychiatry Child Psychiatry
ICU/Sanatorium	Adult Intensive Care Medicine Pediatric Intensive Care Medicine Internal Medicine Neonatology
Pathologists/Radiologists	Laboratory Technicians, Anatomical Pathologist, Microbiologist Medical Radiologist
Residents	Anesthetic Surgical Resident Medical Specialties Resident

Cuadro A.3: Multiemployment of medical workers in IAMC institutions in 2008

	All		Women		Men	
Number of positions	Physicians	%	Physicians	%	Physicians	%
1	3,338	49 %	1,822	52 %	1,516	46 %
2	1,875	28 %	956	27 %	919	28 %
3	898	13 %	446	13 %	452	14 %
4	392	6 %	163	5 %	229	7 %
5	161	2 %	62	2 %	99	3 %
6	68	1 %	22	1 %	46	1 %
7 and more	37	1 %	6	0 %	31	1 %
Total	6,769	100 %	3,477	100 %	3,292	100 %

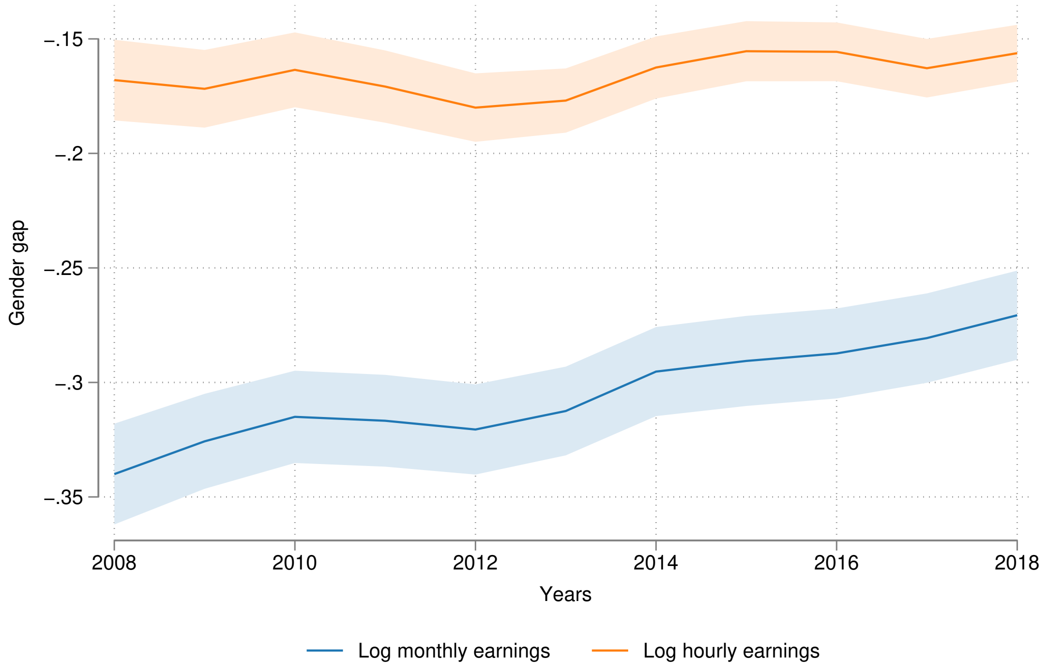
Source: SCARH.

Cuadro A.4: CAD positions by year and specialty

Specialty	2013	2014	2015	2016	2017	2018
General Medicine	40 %	39 %	33 %	32 %	28 %	25 %
Pediatrics	44 %	40 %	33 %	29 %	25 %	22 %
Internal Medicine	16 %	10 %	10 %	12 %	10 %	11 %
Adult Intensive Care	0 %	6 %	9 %	8 %	10 %	11 %
Neonatology	0 %	1 %	4 %	4 %	5 %	5 %
Cardiology	0 %	0 %	0 %	0 %	2 %	3 %
Psychiatry	0 %	0 %	1 %	2 %	3 %	3 %
Pediatric Intensive	0 %	1 %	4 %	4 %	3 %	3 %
Family Medicine	0 %	1 %	3 %	3 %	2 %	2 %
Oncology	0 %	0 %	0 %	0 %	1 %	2 %
Gynecotology	0 %	1 %	1 %	2 %	1 %	2 %
Others	0 %	0 %	0 %	3 %	9 %	12 %
Total CAD	77	597	1,497	1,887	2,562	3,326
Total positions	49,620	50,186	50,390	51,557	53,620	54,403
% CAD	0 %	1 %	3 %	4 %	5 %	6 %

Source: SCARH.

Figura A.1: Gross gender pay gap



Note: The lines report coefficients of the binary variable Female in an OLS regression without control variables, with their confidence intervals (shadows, robust standard errors). Source: SCARH.

Cuadro A.5: Positions by medical specialty

Especialidad	2008 Freq.	2008 Percent	2018 Freq.	2018 Percent
General Medicine	9,012	24.8 %	14,223	26.1 %
Pediatrics	3,450	9.5 %	4,933	9.1 %
Surgery	2,829	7.8 %	3,479	6.4 %
Gynecology	2,234	6.1 %	2,913	5.4 %
Intensive Care Medicine	1,712	4.7 %	2,574	4.7 %
Anesthesiology	1,388	3.8 %	2,280	4.2 %
Other Surgical-Anesthesia	1,098	3.0 %	2,011	3.7 %
Psychiatry	1,161	3.2 %	1,848	3.4 %
Traumatology-Orthopedics	1,218	3.4 %	1,749	3.2 %
Ophthalmology	1,231	3.4 %	1,706	3.1 %
Cardiology	1,212	3.3 %	1,555	2.9 %
Internal Medicine	958	2.6 %	1,374	2.5 %
Directors and Chiefs	596	1.6 %	1,109	2.0 %
Otorhinolaryngology	792	2.2 %	1,033	1.9 %
Dermatology	561	1.5 %	1,013	1.9 %
Radiologist	406	1.1 %	881	1.6 %
Endocrinology	458	1.3 %	836	1.5 %
Urology	662	1.8 %	819	1.5 %
Anatomic Pathologist	595	1.6 %	722	1.3 %
Neurology	527	1.5 %	700	1.3 %
Gastroenterology	378	1.0 %	688	1.3 %
Nephrology	565	1.6 %	665	1.2 %
Neonatology	344	1.0 %	656	1.2 %
Hematology	329	0.9 %	533	1.0 %
Oncology	382	1.1 %	529	1.0 %
Physiatry	437	1.2 %	494	0.9 %
Pneumology	215	0.6 %	280	0.5 %
Residents	-	-	428	0.5 %
Neuropediatrics	126	0.4 %	244	0.5 %
Family Medicine	-	-	187	0.3 %
Physiotherapist/Hemotherapist	281	0.8 %	151	0.3 %
Infectology	35	0.1 %	119	0.2 %
Others	1,206	3.3 %	1,838	3.4 %
Total	36,398	100 %	54,403	100 %

Source: SCARH.

Cuadro A.6: Descriptive statistics for average female position per year

Year	Log monthly income	Log hourly income	Age	Hours	Surgical act	Non-surgical act
2008	10.8	7.1	47	72	1	62
2009	10.8	7.1	47	69	1	64
2010	10.7	7.1	46	68	1	68
2011	10.8	7.1	46	68	1	81
2012	10.8	7.1	46	67	1	72
2013	10.8	7.2	46	67	1	70
2014	10.9	7.2	46	67	1	70
2015	10.9	7.2	45	70	1	75
2016	10.9	7.2	45	70	1	69
2017	10.9	7.2	45	69	1	68
2018	10.9	7.2	45	68	1	67

Source: SCARH.

Cuadro A.7: Descriptive statistics for average male position per year

Year	Log monthly income	Log hourly income	Age	Hours	Surgical act	Non-surgical act
2008	11.1	7.3	50	86	3	81
2009	11.1	7.3	50	82	2	77
2010	11.1	7.3	50	82	2	85
2011	11.1	7.3	50	83	3	94
2012	11.1	7.3	49	81	3	84
2013	11.1	7.4	49	80	3	79
2014	11.2	7.3	49	80	3	76
2015	11.2	7.3	49	80	3	81
2016	11.2	7.3	49	80	3	73
2017	11.2	7.4	49	78	2	69
2018	11.2	7.4	48	77	2	70

Source: SCARH.

Cuadro A.8: Coefficients form Model 1: OLS regression of log monthly wages

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Female	-0.082***	-0.084***	-0.078***	-0.083***	-0.090***	-0.098***	-0.091***	-0.093***	-0.094***	-0.099***	-0.100***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age	0.054***	0.046***	0.051***	0.054***	0.055***	0.044***	0.035***	0.029***	0.028***	0.043***	0.036***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hours	0.004***	0.004***	0.004***	0.004***	0.005***	0.004***	0.004***	0.006***	0.006***	0.006***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Surgical act	0.024***	0.025***	0.025***	0.027***	0.026***	0.024***	0.025***	0.028***	0.026***	0.036***	0.032***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Non-surgical act	0.000***	0.000***	0.000***	0.000***	0.000***	0.002***	0.002***	0.001***	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAD						0.863***	0.634***	0.564***	0.500***	0.515***	0.397***
						(0.060)	(0.024)	(0.015)	(0.016)	(0.019)	(0.024)
Cons	9.154***	9.392***	9.249***	9.248***	9.253***	9.540***	9.741***	9.817***	9.872***	9.595***	9.680***
	(0.091)	(0.081)	(0.075)	(0.074)	(0.072)	(0.070)	(0.069)	(0.068)	(0.068)	(0.070)	(0.068)
Obs.	36,398	42,302	44,373	45,171	47,876	49,620	50,186	50,390	51,557	53,620	54,403
R2	0.51	0.49	0.49	0.50	0.50	0.53	0.56	0.59	0.59	0.58	0.60

Robust standard errors in parentheses

The dependent variable is the logarithm of the monthly wage, and the controls are those specified in Equation 1. For simplicity of presentation, results for specialty, institution and type of contract are omitted.

$^{*}p < 0{,}1$, $^{**}p < 0{,}05$, $^{***}p < 0{,}01$

Source: SCARH.

Cuadro A.9: Coefficients form Model 2: OLS regression of log hourly wages

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Female	-0.059***	-0.059***	-0.053***	-0.053***	-0.055***	-0.061***	-0.062***	-0.056***	-0.051***	-0.052***	-0.057***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Age	0.037***	0.043***	0.047***	0.042***	0.041***	0.034***	0.032***	0.015***	0.020***	0.029***	0.025***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Age2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-surgical act	-0.000***	-0.000***	-0.000***	-0.000***	0.000	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAD						0.119***	0.161***	0.189***	0.152***	0.113***	0.046***
						(0.030)	(0.012)	(0.010)	(0.009)	(0.010)	(0.012)
Cons	5.805***	5.732***	5.734***	5.887***	5.961***	6.123***	6.180***	6.600***	6.516***	6.399***	6.460***
	(0.094)	(0.083)	(0.077)	(0.073)	(0.067)	(0.064)	(0.062)	(0.060)	(0.058)	(0.059)	(0.057)
Obs.	36,398	42,302	44,373	45,171	47,876	49,620	50,186	50,390	51,557	53,620	54,403
R2	0.23	0.22	0.22	0.21	0.22	0.23	0.23	0.26	0.28	0.28	0.28

Robust standard errors in parentheses

The dependent variable is the logarithm of the hourly wage, and the controls are those specified in Equation 1. For simplicity of presentation, results for specialty, institution and type of contract are omitted.

*$p < 0{,}1$, **$p < 0{,}05$, ***$p < 0{,}01$

Source: SCARH.

Cuadro A.10: Duncan's and Karmel and Maclachlan's Indices

Year	ID			KM		
	Index	Confidence intervals 95 %		Index	Confidence intervals 95 %	
2008	0.3184	0.3093	0.3271	0.1590	0.1543	0.1634
2009	0.3164	0.3073	0.3257	0.1582	0.1536	0.1628
2010	0.3109	0.3012	0.3191	0.1554	0.1505	0.1595
2011	0.3022	0.2936	0.3099	0.1508	0.1464	0.1547
2012	0.2956	0.2868	0.3007	0.1472	0.1430	0.1497
2013	0.3020	0.2939	0.3105	0.1501	0.1462	0.1543
2014	0.2854	0.2762	0.2910	0.1417	0.1371	0.1444
2015	0.2820	0.2723	0.2883	0.1398	0.1351	0.1429
2016	0.2887	0.2793	0.2957	0.1426	0.1381	0.1461
2017	0.2868	0.2775	0.2944	0.1413	0.1367	0.1450
2018	0.2843	0.2747	0.2913	0.1397	0.1350	0.1431

DI and KM indices based on Equations B.1 and B.2.

Confidence intervals calculated using bootstrap (500 replications)

Source: SCARH.)

Cuadro A.11: Decomposition of DI effects

Components	Variation 2018 vs 2008	% impact on DI variation
Sex	-5 %	50 %
Ocuppation	-3 %	25 %
Residual	-3 %	25 %
DI	-11 %	100 %

Source: SCARH.

Cuadro A.12: Coefficients form Model 4: OLS regression of log hourly wages

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Female	-0.057***	-0.065***	-0.054***	-0.047***	-0.047***	-0.052***	-0.057***	-0.048***	-0.041***	-0.046***	-0.050***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age	0.053***	0.055***	0.060***	0.061***	0.060***	0.048***	0.049***	0.047***	0.053***	0.057***	0.052***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Age2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-surgical act	-0.000***	-0.000*	-0.000***	-0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAD	0.000	0.000	0.000	0.000	0.000	0.101	0.049	0.041**	0.011	0.000	-0.051***
						(0.087)	(0.031)	(0.019)	(0.017)	(0.015)	(0.013)
% Fem / special	-0.320***	-0.304***	-0.290***	-0.348***	-0.406***	-0.389***	-0.353***	-0.410***	-0.470***	-0.503***	-0.472***
	(0.023)	(0.022)	(0.022)	(0.021)	(0.020)	(0.019)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
% Fem / institu.	0.884***	1.331***	0.688***	0.500***	-0.164**	0.132**	0.752***	0.836***	0.686***	0.642***	1.011***
	(0.077)	(0.082)	(0.078)	(0.072)	(0.069)	(0.066)	(0.071)	(0.070)	(0.065)	(0.065)	(0.064)
Montevideo	-0.070***	-0.067***	-0.053***	-0.019**	-0.009	0.039***	0.014*	-0.002	0.055***	0.083***	0.089***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Cons	5.326***	5.063***	5.319***	5.412***	5.857***	5.962***	5.599***	5.710***	5.664***	5.613***	5.496***
	(0.098)	(0.090)	(0.086)	(0.080)	(0.076)	(0.072)	(0.072)	(0.072)	(0.069)	(0.069)	(0.067)
Obs.	36,398	42,302	44,373	45,171	47,876	49,620	50,186	50,390	51,557	53,620	54,403
R2	0.08	0.09	0.09	0.09	0.08	0.09	0.09	0.09	0.09	0.09	0.1

Robust standard errors in parentheses.

The dependent variable is the logarithm of the hourly wage, and the controls are those specified in Equation 2. For simplicity of presentation, results for type of contract are omitted.

*$p < 0{,}1$, **$p < 0{,}05$, ***$p < 0{,}01$

Source: SCARH.

Cuadro A.13: Decomposition of log hourly income by gender according to Bayard et al. (2003) approach. Relative contribution.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Female	34 %	38 %	33 %	28 %	26 %	29 %	35 %	31 %	27 %	28 %	32 %
Age	106 %	109 %	133 %	135 %	125 %	98 %	113 %	107 %	121 %	119 %	111 %
Age2	-73 %	-78 %	-103 %	-102 %	-98 %	-72 %	-86 %	-83 %	-99 %	-98 %	-91 %
Non-surgical Act	-1 %	0 %	0 %	0 %	0 %	2 %	2 %	1 %	1 %	0 %	1 %
CAD	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
% Woman by specialty	33 %	30 %	29 %	33 %	37 %	36 %	34 %	41 %	47 %	47 %	47 %
% Woman by institution	-7 %	-9 %	-5 %	-4 %	1 %	-1 %	-4 %	-5 %	-5 %	-4 %	-6 %
Montevideo	1 %	1 %	1 %	0 %	0 %	-1 %	0 %	0 %	-1 %	-1 %	-1 %
Substitute	4 %	5 %	8 %	6 %	3 %	3 %	3 %	4 %	3 %	3 %	3 %
Regular substitutes	4 %	4 %	4 %	4 %	4 %	5 %	3 %	5 %	5 %	3 %	3 %
Independient	-2 %	0 %	0 %	0 %	1 %	1 %	0 %	0 %	1 %	2 %	2 %
Total gross income gap	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Total gross income gap in logarithms	-0.1680	-0.1718	-0.1635	-0.1708	-0.1800	-0.1769	-0.1625	-0.1554	-0.1556	-0.1628	-0.1562

Decomposition according to Equation 3.

*$p < 0{,}1$, **$p < 0{,}05$, ***$p < 0{,}01$

Source: SCARH.

Cuadro A.14: Decomposition of log hourly income by gender according to Oaxaca (1973) approach

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Women	7.114***	7.126***	7.114***	7.146***	7.148***	7.178***	7.179***	7.175***	7.192***	7.211***	7.220***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Men	7.282***	7.298***	7.278***	7.317***	7.328***	7.354***	7.342***	7.330***	7.348***	7.373***	7.376***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Difference	-0.168***	-0.172***	-0.164***	-0.171***	-0.180***	-0.177***	-0.162***	-0.155***	-0.156***	-0.163***	-0.156***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Explained	-0.139***	-0.142***	-0.135***	-0.153***	-0.162***	-0.153***	-0.131***	-0.133***	-0.146***	-0.135***	-0.124***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Unexplained	-0.029***	-0.030***	-0.029***	-0.018*	-0.018**	-0.024***	-0.031***	-0.022***	-0.010	-0.027***	-0.032***
	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)

Explained effects attributable to (cont. A.14):

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	-0.130***	-0.145***	-0.152***	-0.154***	-0.157***	-0.106***	-0.151***	-0.134***	-0.163***	-0.151***	-0.147***
	(0.019)	(0.017)	(0.018)	(0.018)	(0.017)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.014)
Age2	0.071***	0.087***	0.102***	0.095***	0.107***	0.059***	0.105***	0.098***	0.130***	0.119***	0.116***
	(0.019)	(0.017)	(0.018)	(0.018)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.015)
Non-surgical act	0.002***	0.001***	0.001***	0.001***	-0.000	-0.003***	-0.002***	-0.001***	-0.001***	-0.001	-0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
% Women/specialty	-0.078***	-0.077***	-0.066***	-0.080***	-0.091***	-0.088***	-0.080***	-0.089***	-0.105***	-0.096***	-0.088***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
% Women/institution	0.013***	0.013***	0.007***	0.005***	-0.001	0.003***	0.009***	0.010***	0.010***	0.009***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Montevideo	-0.001**	-0.001***	-0.000**	0.000	0.000	0.001***	0.000**	0.000	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rest of the country	-0.001**	-0.001***	-0.000**	0.000	0.000	0.001***	0.000**	0.000	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Permanent	0.001	0.005***	0.002	-0.000	0.001	-0.002**	-0.004***	-0.007***	-0.003***	-0.002**	-0.002***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Substitute	-0.013***	-0.014***	-0.018***	-0.012***	-0.008***	-0.005***	-0.003***	-0.002***	-0.002***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Regular Substitute	-0.009***	-0.012***	-0.010***	-0.009***	-0.011***	-0.010***	-0.006***	-0.007***	-0.009***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Independent	0.005***	0.001	0.001	0.000	-0.003***	-0.003***	-0.001	-0.001***	-0.004***	-0.005***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
CAD						0.000**	0.000**	0.000**	0.000*	-0.001***	-0.001***
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Unexplained effects attributable to (cont. A.14):

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Age	1.929***	1.651***	2.077***	2.307***	1.830***	1.796***	0.842***	0.688***	0.450*	0.936***	0.697***
	(0.393)	(0.340)	(0.320)	(0.303)	(0.279)	(0.269)	(0.263)	(0.258)	(0.253)	(0.253)	(0.242)
Age2	-1.033***	-0.898***	-1.075***	-1.212***	-0.942***	-0.920***	-0.433***	-0.324**	-0.219*	-0.424***	-0.352***
	(0.196)	(0.170)	(0.161)	(0.153)	(0.141)	(0.135)	(0.132)	(0.130)	(0.126)	(0.126)	(0.120)
Non-surgical act	0.013***	0.008**	0.004**	0.004***	0.012***	0.026**	0.018***	0.012***	0.015***	-0.030***	0.014
	(0.005)	(0.003)	(0.002)	(0.002)	(0.004)	(0.011)	(0.006)	(0.004)	(0.006)	(0.009)	(0.011)
% Women/specialty	0.165***	0.182***	0.125***	0.168***	0.184***	0.186***	0.194***	0.199***	0.239***	0.138***	0.117***
	(0.027)	(0.026)	(0.026)	(0.025)	(0.025)	(0.023)	(0.023)	(0.022)	(0.022)	(0.023)	(0.022)
% Women/institution	-0.111	0.146*	0.057	0.090	-0.050	-0.142*	-0.285***	-0.259***	-0.252***	-0.258***	-0.226***
	(0.074)	(0.083)	(0.084)	(0.081)	(0.076)	(0.074)	(0.079)	(0.078)	(0.074)	(0.075)	(0.074)
Montevideo	0.010***	0.005*	0.005*	0.010***	0.009***	0.003	0.005**	0.004	0.005*	0.010***	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Rest of the country	-0.022***	-0.012*	-0.011*	-0.021***	-0.018***	-0.006	-0.011**	-0.008	-0.009*	-0.020***	-0.013**
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Permanent	0.005	0.006	-0.003	0.002	0.001	-0.003	-0.012**	-0.011*	0.000	0.003	-0.004
	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Substitute	0.029***	0.020***	0.022***	0.013***	0.007**	0.007**	0.004	0.002	-0.003	0.004	0.008***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Regular Substitute	0.015***	0.018***	0.017***	0.018***	0.026***	0.017***	0.016***	0.019***	0.024***	0.030***	0.027***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Independent	-0.020***	-0.020***	-0.017***	-0.017***	-0.019***	-0.012***	-0.011***	-0.010***	-0.013***	-0.018***	-0.018***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CAD						-0.000	-0.000	0.000	-0.001	0.003***	0.002
						(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Cons	-1.009***	-1.136***	-1.230***	-1.379***	-1.058***	-0.975***	-0.358**	-0.334**	-0.245*	-0.402***	-0.291**
	(0.210)	(0.189)	(0.183)	(0.173)	(0.161)	(0.156)	(0.155)	(0.152)	(0.148)	(0.149)	(0.145)
Obs.	36,398	42,302	44,373	45,171	47,876	49,620	50,186	50,390	51,557	53,620	54,403

Robust standard errors in parentheses.
Decomposition according to Equation 4.
*$p < 0{,}1$, **$p < 0{,}05$, ***$p < 0{,}01$

Cuadro A.15: Overall and detailed decomposition of (log) hourly earnings by gender accounting for medical specialties (selected years)

	2008	2013	2018
Overall			
Women	7.114***	7.178***	7.220***
	(0.006)	(0.005)	(0.004)
Men	7.282***	7.354***	7.376***
	(0.007)	(0.005)	(0.005)
Observed difference	-0.168***	-0.177***	-0.156***
	(0.009)	(0.007)	(0.006)
Explained effect	-0.122***	-0.142***	-0.103***
	(0.007)	(0.005)	(0.005)
Unexplained effect	-0.046***	-0.035***	-0.053***
	(0.010)	(0.008)	(0.006)
Explained			
Age	-0.076***	-0.059***	-0.066***
	(0.018)	(0.015)	(0.013)
Age sq.	0.021	0.010	0.040***
	(0.018)	(0.015)	(0.013)
Non-surgical act	0.002***	-0.003***	-0.002**
	(0.000)	(0.001)	(0.001)
Directors/Chiefs	0.001*	0.001**	-0.002***
	(0.000)	(0.000)	(0.001)
General Medicine	0.001	0.002***	-0.001**
	(0.001)	(0.001)	(0.000)
Pediatrics/Family Med.	-0.010***	-0.015***	0.004**
	(0.003)	(0.003)	(0.002)
AS	-0.078***	-0.077***	-0.103***
	(0.004)	(0.003)	(0.003)
MS	0.020***	0.011***	0.022***
	(0.002)	(0.002)	(0.002)
ICU/Internal Medicine	-0.001***	-0.001***	0.000**
	(0.000)	(0.000)	(0.000)
Pathologists/Radiologists	-0.001**	0.000	0.004***
	(0.000)	(0.000)	(0.001)
Residents	0.000	0.000	-0.005***
	(.)	(.)	(0.001)
CAD		0.000**	0.001**
		(0.000)	(0.000)
Unexplained			
Age	1.288***	1.642***	0.160
	(0.380)	(0.259)	(0.229)
Age sq.	-0.716***	-0.838***	-0.087
	(0.190)	(0.130)	(0.113)

Non-surgical act	0.007*	0.022*	0.015
	(0.004)	(0.012)	(0.011)
Directors/Chiefs	0.000	-0.001**	0.000
	(0.001)	(0.001)	(0.001)
General Medicine	0.005	0.019***	-0.001
	(0.007)	(0.005)	(0.004)
Pediatrics/Family Med.	-0.001	0.019***	-0.007**
	(0.006)	(0.004)	(0.003)
AS	0.011**	0.003	-0.002
	(0.005)	(0.004)	(0.003)
MS	0.011	0.012**	0.004
	(0.008)	(0.006)	(0.004)
ICU/Internal Medicine	0.002	0.008***	0.005***
	(0.003)	(0.002)	(0.002)
Pathologists/Radiologists	-0.005***	-0.005***	-0.011***
	(0.002)	(0.001)	(0.001)
Residents	0.000	0.000	0.002***
	(.)	(.)	(0.000)
CAD		-0.000**	0.001
		(0.000)	(0.001)
Constant	-0.676***	-0.842***	-0.130
	(0.194)	(0.131)	(0.115)
Observations	36398	49620	54403
Institutions	Yes	Yes	Yes
Type of labor contract	Yes	Yes	Yes

Robust standard errors in parentheses
Source: SCARH
Separate regressions for females and males. The dependent variable is the logarithm of the hourly wage, and the controls are those specified in Equation 1. For simplicity of presentation, results for institution and type of contract omitted in the detailed decomposition.
* $p < 0{,}10$, ** $p < 0{,}05$, *** $p < 0{,}01$

Cuadro A.16: Coefficients from unconditional quantile regression of log hourly wage (selected quantiles and years)

	2008			2018		
	Q10	Q50	Q90	Q10	Q50	Q90
Female	-0.003	-0.043***	-0.160***	-0.013	-0.024***	-0.189***
	(0.016)	(0.010)	(0.023)	(0.008)	(0.005)	(0.016)
Age	0.089***	0.028***	-0.011	0.052***	0.018***	-0.006
	(0.008)	(0.004)	(0.009)	(0.004)	(0.002)	(0.006)
Age sq.	-0.001***	-0.000***	0.000***	-0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-surgical act	-0.000**	-0.000***	-0.000***	0.001***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAD	0.000	0.000	0.000	0.221***	0.178***	-0.380***
	(0.000)	(0.000)	(0.000)	(0.013)	(0.023)	(0.019)
Constant	3.896***	6.048***	7.692***	5.077***	6.691***	8.016***
	(0.195)	(0.092)	(0.216)	(0.083)	(0.045)	(0.140)
Observations	36398	36398	36398	54402	54402	54402

Bootstrapped standard errors in parentheses (500 replications)

* $p < 0{,}10$, ** $p < 0{,}05$, *** $p < 0{,}01$. **Source**: SCARH.

The dependent variable is the logarithm of the hourly earnings. Controls for physician specialty, healthcare institution, and type of contract are also included in the regression but not reported here. Complete estimations for the other years of the sample are also available under request.

Cuadro A.17: Aggregate decomposition of hourly earnings by gender - Selected years and quantiles

	2008			2018		
	Q10	Q50	Q90	Q10	Q50	Q90
Women	6.152***	7.076***	8.171***	6.463***	7.214***	8.061***
Men	6.235***	7.222***	8.495***	6.481***	7.302***	8.423***
Observed difference	-0.084***	-0.146***	-0.324***	-0.018	-0.088***	-0.362***
Total composition effect	-0.108***	-0.138***	-0.144***	-0.024**	-0.083***	-0.161***
Pure composition effect	-0.101***	-0.127***	-0.118***	-0.023***	-0.101***	-0.154***
Specification error	-0.007	-0.011*	-0.025**	-0.001	0.017***	-0.006
Total wage structure effect	0.025	-0.008	-0.180***	0.005	-0.004	-0.201***
Reweighting error	-0.006	-0.002	-0.012**	0.001	0.005***	0.010***
Pure wage struc. eff.	0.031	-0.006	-0.168***	0.004	-0.010	-0.211***

Bootstrapped standard errors (500 replications) were computed to calculate p-values. * $p < 0{,}10$, ** $p < 0{,}05$, *** $p < 0{,}01$. **Source**: SCARH.
The dependent variable is the logarithm of the hourly earnings. Separate regressions for females and males are estimated according to equation 1. Estimations for other years of the sample are also available under request.

Cuadro A.18: Detailed decomposition of hourly earnings by gender - Selected years and quantiles

	2008			2018		
	Q10	Q50	Q90	Q10	Q50	Q90
Composition effect:						
Age	-0.041***	-0.045***	-0.074***	-0.019***	-0.017***	-0.063***
CAD	0.000	0.000	0.000	0.005***	0.001*	-0.006***
Directors/Chiefs	0.002*	-0.001*	0.002*	-0.001	-0.002***	0.002
General Medicine	0.001	0.001	0.001	0.001*	-0.002**	-0.002**
Pediatrics/Family Med.	-0.010	-0.009**	-0.003	0.047***	-0.011***	-0.015***
AS	-0.066***	-0.083***	-0.086***	-0.106***	-0.082***	-0.066***
MS	0.003	0.024***	0.023***	0.033***	0.016***	0.002
ICU/Internal Medicine	0.001**	-0.004***	-0.001	0.003**	-0.002**	-0.002**
Pathologists/Radiologists	-0.000	-0.001*	-0.001	0.004***	0.003***	0.004***
Residents	0.000	0.000	0.000	-0.009***	-0.002***	-0.000
Health institution	0.018***	0.011***	0.008	0.019***	0.008***	0.000
Type of labor contract	-0.009*	-0.020***	0.012	-0.001	-0.012***	-0.008**
Specification error	-0.007	-0.011*	-0.025**	-0.001	0.017***	-0.006
Wage structure effect:						
Age	0.780	0.153	0.551	0.210	0.067	-0.470
CAD	0.000	0.000	0.000	0.002	-0.009***	0.013***
Directors/Chiefs	0.001	-0.002*	0.003*	0.001	-0.001*	0.002
General Medicine	-0.011	0.013*	-0.001	-0.019*	0.014***	0.028**
Pediatrics/Family Med.	0.010	0.007	0.000	0.001	0.006*	-0.005
AS	0.016*	0.012*	-0.018	0.005	-0.006	0.006
MS	0.050***	0.032***	-0.011	0.011	0.009**	0.001
ICU/Internal Medicine	-0.004	0.007	0.005	-0.004	0.011***	0.010**
Pathologists/Radiologists	-0.011**	-0.006**	-0.006	-0.011***	-0.010***	-0.012**
Residents	0.000	0.000	0.000	0.002	0.001***	0.000
Health institution	0.012	0.006	-0.006	0.022*	0.006	-0.013
Type of labor contract	0.030	0.012	0.107***	-0.001	-0.009*	0.005
Constant	-0.842	-0.238	-0.791	-0.213	-0.089	0.225
Reweighting error	-0.006	-0.002	-0.012**	0.001	0.005***	0.010***

Bootstrapped standard errors (500 replications) were computed to calculate p-values. * $p < 0{,}10$, ** $p < 0{,}05$, *** $p < 0{,}01$. **Source**: SCARH.
The dependent variable is the logarithm of the hourly earnings. Separate regressions for females and males are estimated according to equation 1. Reweighting factors estimated via logit regression as described in Firpo et al. (2018). Categorical variables are normalized following Yun (2005).
Estimations for other years of the sample are also available under request.

B Appendix: Methodological complement

B.1 Segregation Indices

In this section, we provide a brief description of the two segregation indices used to measure horizontal segregation. The first one, proposed by Duncan and Duncan (1955), was originally designed to measure the degree of residential segregation by race. When applied to the labor market, and to gender medical labor segregation by specialty in particular, the Duncan Index measures the percentage of the female workforce who would have to switch from one group (specialty) to another to achieve an equal distribution by gender. The index is defined as follows:

$$DI = 1/2 \sum_{g} |m_g - f_g| \tag{B.1}$$

Where m_g is the proportion of males working in a group (specialty) g over the total number of males, and f_g is the proportion of women. A value of 0 in the DI implies that the distribution between men and women by group (specialty) is identical, while a value of 1 indicates total segregation. An important limitation of the DI is its sensitivity to the level of aggregation of the groups.[9] To correct this problem, a usual alternative [10] consists of decomposing the DI in three parts: i) a *gender effect*, which quantifies the change in the gender composition of the groups given constant the occupational structure; ii) a *composition effect*, that reflects the effect of a change in the occupational structure of the specialties if the gender composition is kept constant, and iii) a *residual effect*, the part of the change in the DI that is not explained by any of the previous effects. Expressions for gender and occupation effects are the following:

$$gender_e f = \frac{1}{2}\left[\sum_{p}\left|\frac{m_{p2}T_{p1}}{\sum_p m_{p2}T_{p1}} - \frac{f_{p2}T_{p1}}{\sum_p f_{p2}T_{p1}}\right| - \sum_{p}\left|\frac{m_{p1}T_{p1}}{\sum_p m_{p1}T_{p1}} - \frac{f_{p1}T_{p1}}{\sum_p f_{p1}T_{p1}}\right|\right]$$

$$occup_e f = \frac{1}{2}\left[\sum_{p}\left|\frac{m_{p1}T_{p2}}{\sum_p m_{p1}T_{p2}} - \frac{f_{p1}T_{p2}}{\sum_p f_{p1}T_{p2}}\right| - \sum_{p}\left|\frac{m_{p1}T_{p1}}{\sum_p m_{p1}T_{p1}} - \frac{f_{p1}T_{p1}}{\sum_p f_{p1}T_{p1}}\right|\right]$$

Where p is the group (specialty), T is the occupational structure (number of workers in group p), and subscripts 1 and 2 identify the different time periods.

An alternative index to the DI is the one proposed by Karmel and Maclachlan (1988). This indicator corrects the DI values by taking into account the relative size of females and males in

[9] This means that an increase or decrease in the DI can be explained by changes in the gender composition within each group (specialty), as well as by changes in the participation of the group (specialty) in the total number of population (physicians). For example, in our study, if between years' t and $t+1$, there is an increase in the numbers of workers in a low segregated specialty, the DI would show a decrease with no change in gender shares within specialties.

[10] For an application of this decomposition see Katzkowicz y Querejeta (2012) y Amarante y Espino (2001).

the total number of workers.

$$KM = \frac{1}{T}\sum_{g} |am_g - (1-a)f_g| = 2a(1-a)DI \tag{B.2}$$

Where a represents the proportion of females in overall workforce (physician positions) T.