Gender gaps in a highly qualified sector: evidence from administrative data

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Abstract

This paper studies the existence of gender income 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. We estimate the gross and conditional pay gender gap among physicians for the entire period between 2008 and 2018. Furthermore, we evaluate two potential mechanisms that could explain part of the differences in physician earnings, specifically, horizontal segregation (the concentration of women in certain specialties with lower salaries) and vertical segregation (the underrepresentation of women in top hierarchical positions). Our results indicate that there are differences in income between female and male physicians and that both horizontal and vertical segregation play a role in explaining these gaps.

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

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1. Introduction

The participation of women in the Latin American labor market has grown significantly in the last half century, with an increasing number of women entering highly prestigious occupations (Goldin, 2014). However, despite this progress, differences in the outcome variables of men and women in the labor market still exist and the process of convergence has slowed since the 1990s (Goldin, 2014; Marchionni et al., 2019). Women have lower participation rates, work fewer hours and earn less than men. Additionally, 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 labor income gaps remain even in the skilled population, showing that higher educational level of women is not enough to eliminate wage gender gaps.

The literature on gender gaps in the labor market is extensive, but there is a lack of research on what happens within specific occupations (Goldin, 2014). We study the existence of gender gaps within a highly skilled profession and understand whether the way an occupation is structured may impact income equality. Our objective is to study the income gaps between men and women among Uruguayan physicians, a sector with high female participation and a high level of qualification in a developing country. To answer this question, we will use data from the Human Resources Control and Analysis System (*SCARH*, for its acronym in Spanish) database, published by the Ministry of Public Health. This administrative registry contains information on private health sector workers for Collective Medical Assistance Institutions (*IAMC*, for its acronym in Spanish) and health insurance between 2008 and 2018. These records will allow us to observe all the income of physicians working in the private subsector.

We begin by estimating the gross and conditional pay gender gap among physicians for the entire period, using ordinary least squares models. Next, we evaluated two potential mechanisms that could explain part of the differences in physician earnings. First, given that physicians work in different specialties, the differences in earnings could be due to a higher concentration of women in those specialties with lower salaries. This concentration of women in certain specialties may be due to discrimination, preferences for specialties that have schedules and work patterns more compatible with family life, or differences in preferences and tastes (Magnusson, 2016). If female-dominated occupations have lower pay, the difference is greater, which is known as horizontal segregation. To determine the existence of horizontal segregation, we calculate the Duncan, and Karmel and Maclachlan segregation indices for each year of the sample. Additionally, we estimate the influence of horizontal segregation on the wage 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 specialties to the overall gender gap. Second, the underrepresentation of women in top hierarchical positions could be a contributing factor to the gaps in the healthcare sector. Despite women's increasing education and experience, they are still underrepresented in higher-paid positions (Marchionni et al., 2019). Therefore, we evaluate whether there are differences in the representation of women and men along the hierarchical scale that is transversal to the specialties, known as vertical segregation or the glass ceiling. This barrier explains a significant portion of the 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 income between female and male physicians even after controlling for observable characteristics of the individual and the field of medicine, such as medical specialty. We did not observe a decrease in the conditional gap over this period. We found evidence that segregation by specialty contributes significantly to explaining the gender gap in physician earnings. Furthermore, our estimates are consistent with the presence of a glass ceiling for female medical workers.

This paper contributes to the literature on gender wage gaps (Goldin, 2014; Blau & Kahn 2017). A significant portion of this literature has focused on studying the importance of occupational segregation as a significant component of the wage gap. In developed countries, it has been observed that occupational segregation, as well as differences within occupations and within firms, are important in explaining the wage gap (Macpherson & Hirsch, 1995; Bayard et al., 2003; Ponthieux & Meurs, 2015). In the US, increasing importance of the gap at the top of the distribution in the total gap is found (Blau & Kahn, 2017), highlighting explanations such as temporary breaks in work and shorter hours worked by women, mainly for high-skilled workers, gender roles, their consequent division of labor and occupational segregation, and the existence of discrimination. In Latin America, the sectoral structure of the labor market differs by sex, and women tend to work in more flexible jobs than men in terms of the organization of the working day. The average hourly wage of a woman is on average 22% lower than that of a man when workers with similar characteristics are compared. Although most of this gap corresponds to differences within occupations (Marchionni et al., 2019), 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 labor market plays a role in explaining the income differences between men and women (Bucheli & Rossi, 1985; Furtado & Raffo, 1998; Rivas & Rossi, 2002). More recently, Colacce et al. (2020) found that the gender wage gap is largely explained by the fact that women work fewer hours. However, the difference in hourly income between males and females with the same sociodemographic characteristics amounts to 19%. Regarding the importance of segregation, some studies have found that female wages are negatively affected by the concentration of women in certain occupations, while male wages are not adversely affected by the same conditions (Amarante & Espino, 2004; Katzkowicz & Querejeta, 2013). Occupational segregation and mismatches by qualification have also contributed to explaining a significant portion of the wage gap in Uruguay (Espino, 2013; Espino et al., 2014). Other studies have found that wage gaps controlled by observable characteristics are more important in the upper percentiles of the wage distribution, suggesting the presence of a glass ceiling in Uruguay (Bucheli, 2005; Borrás & Robano, 2010).

More specifically, we add to a strand of literature that studies gender wage differences in the health sector. Previous studies in developed countries have shown that there are salary differences between male and female physicians that are not only due to their observable characteristics but also attributed to different factors such as different specialty 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 more scarce, but it has been observed in Peru (Amaya & 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 on gender gaps within a highly qualified profession in a developing country. Although the gender wage 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 its own. The labor 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 characterized by a high participation of female workers, a phenomenon that has increased recently (Mora et al., 2018). However, there are gender-related differences in the type of positions held by workers, either among the different specialties 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 income gap. This paper contributes to generating useful information for policy makers, both those responsible for training and employment, to guide the design of instruments that can correct gender inequality. Labor 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 organized as follows. Section 2 presents a description of the labor market of the health sector. Section describes 3 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. Labor market in the healthcare sector in Uruguay

The healthcare market in Uruguay has two subsectors, private and public. Health workers tend to work in both subsectors indistinctively. This section presents a brief explanation of the organization of the labour market in the health sector, focusing on the private subsector (particularly the principal health care institutions, called IAMCs) and physicians.

Human Capital and Employment

The degree of General Practitioner (GP) requires seven years of training. [1] Additionally, to obtain the title of Medical Specialist a GP requires an additional 3 to 6 years of training (depending on the specialty). There are two mechanisms to obtain a specialty: the Conventional Postgraduate Program and the Residency Program. In addition, there are limited access quotas to the postgraduate or residency program per specialty and per year (see Table A.1 and A.2.). General practitioners must take one or more tests and, depending on these results, these quotas for training are allocated.

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

[1] Syllabus of the School of Medicine of the University of the Republic 2008.

a high degree of manual training, such as surgery), others can only be taken through the Postgraduate Program, and others through both systems.[2]

Physicians in Uruguay are characterized by high multi-employment. Most of them have more than one job and each of them 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 the physicians, 48%, have only one job in the private sector, which is reduced by 31% when both the private and public sectors are considered. The multi-employment is slightly more important for men than for women (50% of women hold a single position in the private institutions, while for men it is 45%).

TABLE 1: MULTI-EMPLOYMENT OF MEDICAL WORK IN IAMCS IN 2018.

Number of positions	All		Women		Men	
	Physicians	%	Physicians	%	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 subsector is also illustrated by the relevance of substitutions (incumbent physicians overloaded with several jobs tend to make room for 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.[3] Table 2 shows the average number of hours worked per specialty group and per work modality.

[2] A detailed description of the medical residency market can be found in Contreras and Faggeti (2016), who analyze this market in Uruguay.

[3] 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 specialties differ significantly from each other with respect to working arrangements.

TABLE 2: AVERAGE HOURS WORKED PER MONTH BY SPECIALTY GROUP AND BY AREA AT IAMC IN 2018.

AREA	Directors & Chiefs	General Medicine	Pediatrics & Family Medicine	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 hospitalization	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
Door	0	24	22	2	0	7	1	5
On call Adult ICU	0	1	0	0	0	35	0	39
On call Pediatric ICU	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
TOTALES	109	84	84	58	55	99	80	189

MS = Medical Specialties; AS = Aesthetic and Surgical Specialties. The specialty groups were formed according to the modality of work. Details of the specialty groups are shown in Table 1.1 of Annex 1.
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 specialties where payment per act is predominant). These positions were implemented gradually and by specialty. In private sector, CAD positions predominate in general medicine, pediatrics, internal medicine, and intensive care medicine. In 2018, CAD positions came to represent 6% of private sector positions (see Table A.4).

Salary

In Uruguay there is a collective bargaining system where wages are negotiated. The government, employers and workers participate in this negotiation. The salaries paid to physicians by the mutual insurance companies have two components: one fixed and one variable. Fixed payments refer to a monthly salary or an hourly salary. Variable payments involve a payment for the number of times a service is performed. This service may involve the number of patients seen or it may be due to the performance of a *medical act*. A medical act indicates a specific procedure such as surgery, delivery of a baby, among others. For both fixed and variable remuneration, the level of remuneration depends on the type of activity performed and the medical specialty.

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 specialty. 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).

TABLE 3: INCOME, HOURS WORKED AND ACTS BY POSITION. 2008-2018. MONTHLY AVERAGE. CONSTANT 2018 PESOS.

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

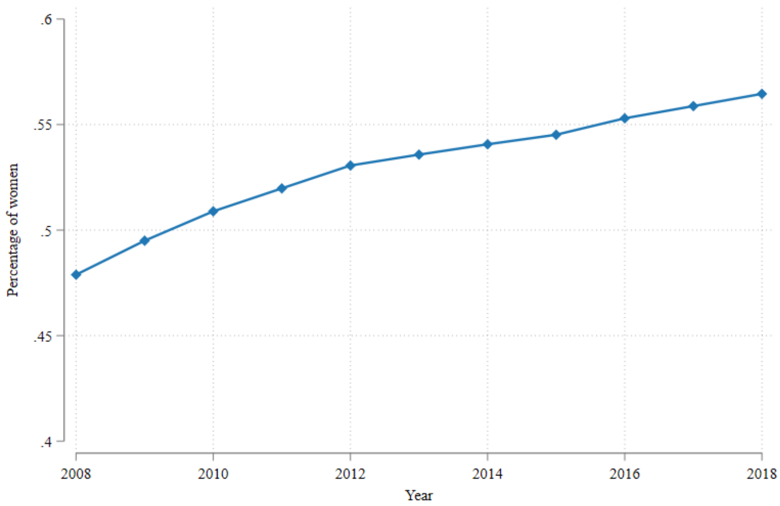
Source: SCARH.

Women's participation

The healthcare sector has historically been feminized. Currently, this feminization 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 (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).

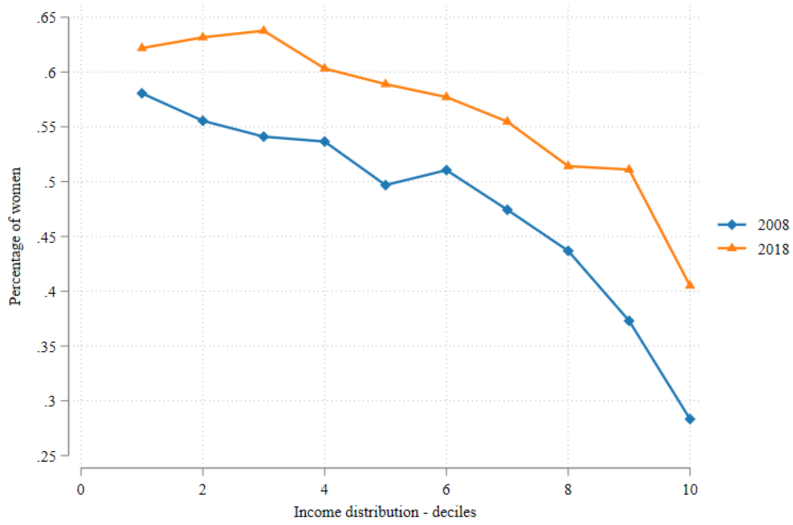
On the other hand, the participation of women decreases when we restrict the population to those receiving the highest incomes (Figure 2). In 2018, approximately 60% of decile 1 (10% lowest income) positions were held by women, while in decile 10 (10% highest income) female participation is 41%. Therefore, 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 specialties (the highest paid positions). In contrast, they are overrepresented in pediatrics and family medicine. This could be due to the fact that some specialties, such as surgical specialties, have barriers to entry for women, and that in the work spaces these are less valued than males (Mora et al., 2018). In addition, the authors raise the difficulty perceived by Uruguayan female physicians to reconcile their career with family life. As a result, when observing the monthly hourly income and the percentage of women by specialty (Figure 3), a negative relationship between the two variables is perceived. In other words, women are employed to a greater extent in specialties with lower hourly incomes.

FIGURE 1: PERCENTAGE OF WOMEN IN TOTAL POSITIONS BY YEAR



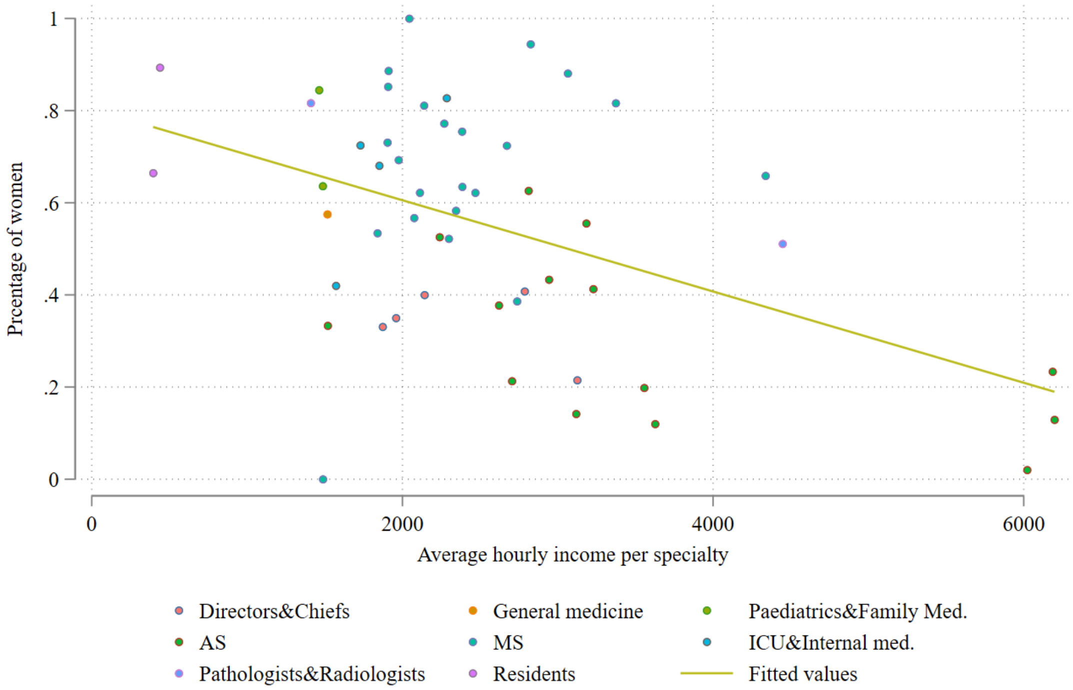
Notes: The figure shows the evolution of the proportion of female physicians in the private sector in Uruguay. *Source:* SCARH.

FIGURE 2: PERCENTAGE OF WOMEN ACROSS THE MONTHLY INCOME DISTRIBUTION IN 2008 AND 2018.



Notes: The figure shows for 2008 and 2018 the proportion of female physicians in each decile of the monthly salary distribution. *Source*: SCARH.

FIGURE 3: PERCENTAGE OF WOMEN AND AVERAGE HOURLY INCOME BY SPECIALTY IN 2018.

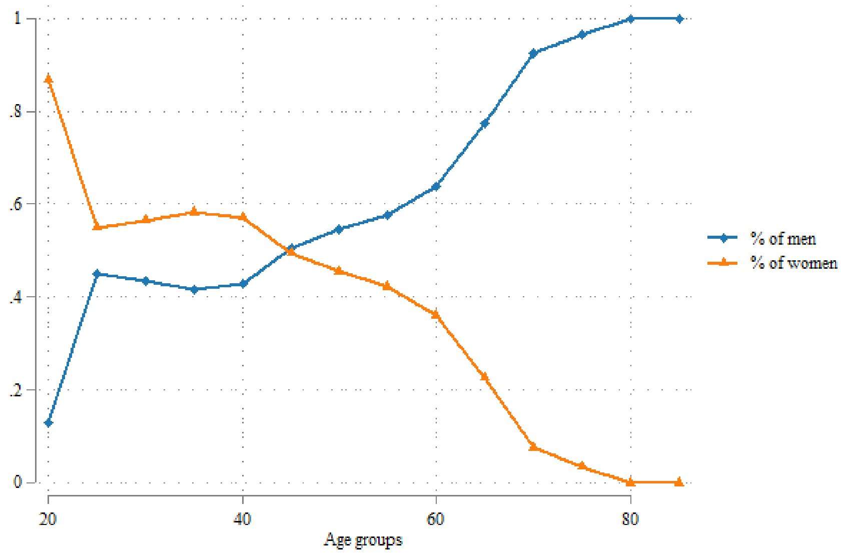


Notes: MS = Medical Specialties; AS = Aesthetic and Surgical Specialties. The specialty groups were formed according to the modality of work. Details of the specialty groups are shown in Table 1.1 of Annex 1. *Source*: SCARH.

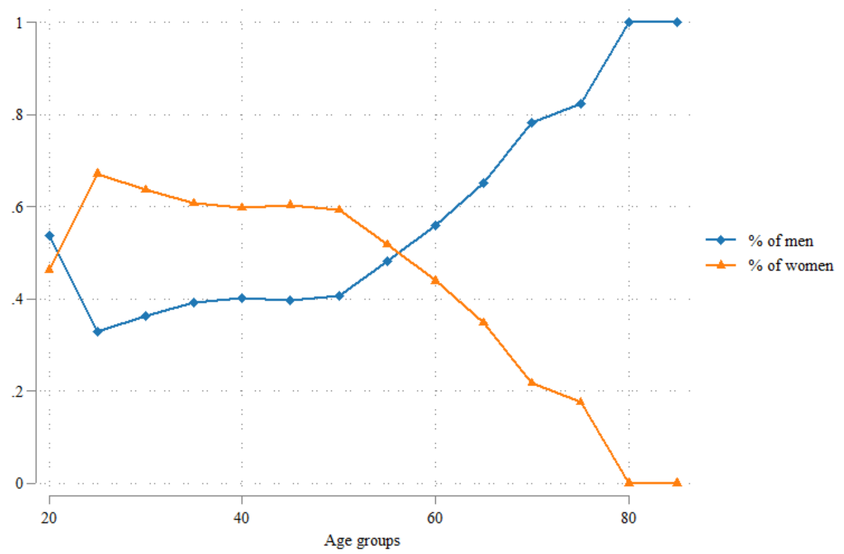
Finally, the age structure of men is older than that of women. Panels a) and b) of Figure 4 presents the percentage of women according to groups of age in 2008 and 2018, respectively. In 2008, it can be seen that women are in the majority in the younger population, up to the 45 to 50 age bracket. After that age, physicians are mostly male. In 2018, the difference occurs ten years later, between 55 and 60 years of age.

FIGURE 4: PERCENTAGE DISTRIBUTION OF MEDICAL POSITIONS BY AGE AND SEX IN 2008 AND 2018.

Panel a) 2008



Panel b) 2018



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

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 represent the main source of information of the present work. Contains data on health human resources in the private sector between 2008 and 2018, for the two main health institutions (IAMCs and Seguros Privados).[4] It includes monthly information on payments, hours worked and acts performed by position, for the months of 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. Since it is possible to identify each worker over the years, the data base consists of an unbalanced panel. In this paper, only data on medical positions are used for estimation purposes.

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

3.2 Methodology

As shown in the previous sections, the preliminary evidence indicates a priori the existence of differences on payments between women and men in the physician labor market. The next sections of this paper first attempt to measure the extent of this gap and then analyze its nature. To this end, we first estimate augmented versions of the traditional Mincer equations. To further characterize these primary results, we then pursue several methodological strategies. Horizontal segregation is assessed using the so-called segregation indices, and following Bayard et al. (2003), the contribution of this segregation to the gender gap is estimated. This is complemented by Oaxaca-Blinder decompositions. To assess the presence of vertical segregation, unconditional quantile regression method, proposed by Firpo et al. (2009), are computed. In addition,

[4] See Section 2 for more details of the health sector in Uruguay.

decompositions based on this quantile regression approach will be performed to disentangle the mechanisms that explain the gender differences between and within medical specialties.

3.2.1 Gender gap

The (conditional) gender gap[5] is estimated by the following linear model:

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

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; the matrix *X* include 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, ϵ_i, is conditionally independent with respect to all covariates.

3.2.2 Horizontal segregation

To determine the existence of horizontal segregation, the Duncan, and Karmel and Maclachlan segregation indices are calculated for each year of the sample. The methodological details of these indices are presented in Appendix B. To determine the influence of horizontal segregation on the wage gap, we then apply the alternative proposed by Bayard et al. (2003). This approach consists in estimating a linear model in which wage differentials are assumed to be a function of individual characteristics and the feminization of different work environments. In this case, feminization is represented in two ways: as a percentage of women in the medical specialty and in the institution.

The regression to be estimated is:

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

Where the variables are the same of equation (1) with the exclusion of dummies for specialty and health care institution. In addition, segregation variables are included: $Fem.Spec_g$ correspond to the percentage of positions held by women in the specialty g, and $Fem.Inst_g$ to the percentage of women in the institution *n*, the two covariates associated to the labor market feminization.

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

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

$$\ln(y_f) - \ln(y_m) \\ = \hat{\beta} + (Fem.Spec_f - Fem.Spec_m)\hat{\gamma} \\ + (Fem.Ins_f - Fem.Ins_m)\hat{\delta} + (X_f - X_m)'\hat{\Lambda} \quad (3)$$

Where the subscripts f and m on the variables indicate the means for women and men, respectively. The decomposition shows how much of the wage gap is explained by the segregation of women into particular specialties 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 sex differences in wages controlling for segregation and the other characteristics $(\hat{\beta})$. While the terms associated to mean differences in segregation and other observable controls can be viewed as a *between* effect, the $\hat{\beta}$ coefficient implicitly represent the sex wage gap *within* covariates cells. Given that $Fem.Spec_f$ and $Fem.Spec_m$ represent 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 health care 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 follow:[6]

$$\ln(y_f) - \ln(y_m) = \hat{\Delta}_O^{\mu} \\ = \Big[(Fem.Spec_f - Fem.Spec_m)\hat{\gamma}_m + (Fem.Ins_f - Fem.Ins_m)\hat{\delta}_m \\ + (X_f - X_m)'\hat{\Lambda}_m\Big] \\ + \big[Fem.Spec_f(\hat{\gamma}_f - \hat{\gamma}_m) + Fem.Ins_f(\hat{\delta}_f - \hat{\delta}_m) + X_f'(\hat{\Lambda}_f - \hat{\Lambda}_m)\big] \\ = \Delta_X^{\mu} + \Delta_S^{\mu} \quad (4)$$

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 Firpo et. al (2011). The term Δ_X^{μ} is the *composition effect*, also called the "quantity effect" or the "explained" (by group differences) part of the

[6] 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).

decomposition. The term Δ_S^{μ} is the *wage structure effect*, also called the "unexplained" part of the wage gap or the portion due to discrimination. As Jan (2008) pointing 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 wage structure. This means, for example, that the explained effect compares men's actual mean outcome with men's counterfactual mean outcome if they had women's covariates ($X_f' B_m - X_m' B_m$).[7] From another point of view, the male coefficients (the male wage structure) are considered as the nondiscriminatory coefficients, i.e., discrimination is assumed to occur directly against women. However, the male wage structure does not necessarily represent the appropriate returns that women would be pay paid if labor market discrimination doesn't exist. Many alternative choices of counterfactuals have been proposed to achieve this kind of issues, based on different election of the nondiscriminatory coefficients (Jan, 2008). To maintain coherence of presentation and comparability with Bayard's decomposition, a simple two-fold approach is adopted here.

The decomposition in equation (4) is a detailed decomposition, which takes into account the contribution of each single or group of covariates to the mean difference in the outcome due to the linear additivity assumption of the OB approach. In the context of this work, detailed decomposition can also help us to answer the question of how much of the overall gender gap is due to the gender composition of each specialty or group of specialties. Or to what extent the evolution in the relative returns to specialties (or groups of) explain the gender pay gap. This implies to move again to a regression with physician specialties as explanatory variables, as in equation (1), estimated separately for women and men, and compute the detailed decomposition based on it. For the sake of a clean interpretation, we perform this detailed decomposition including group of specialties according to the definition presented in Table 2.

Finally, since specialty 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.[8] The usual practice varies according to the specific area, but it is usual to omit the reference category for the rest, or the mode of 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

[7] 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.

[8] 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 specialty case, if General Medicine is omitted, then the coefficient associated to, say, Pediatric, represent the difference in payment between those specialties.

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 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 will adopt the normalization proposed by Firpo et al. (2009).

3.2.2 Vertical segregation

To account for the existence of vertical segregation (i.e different gender gaps along the income distribution), re-centered influence function (RIF) regressions for quantiles, proposed by Firpo et al (2009), are estimated. This approach allows to estimate the partial effects of the covariates on the unconditional quantile of the variable.[9] The method consists on 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 wages. This can be interpreted as evidence in favor 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 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 $RIF(y;v) = v\left(F_y\right) + IF(y;v)$. 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:

$$RIF(y;Q_\tau) = Q_\tau + \frac{\tau - \mathbb{I}\{y \leq Q_\tau\}}{f_y(Q_\tau)}, \qquad (5)$$

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

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

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 $\mathbb{I}\{y \leq Q_\tau\} = 1 - \mathbb{I}\{y \geq Q_\tau\}$, equation (5) can be writing as:

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

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:

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

Thus, the model to the expected RIF implies to estimate a probability model of y conditional on the covariates X. Firpo et al (2009) propose three alternatives to do this (LPM, Logit and 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 $E(u|x) = 0$, we have:

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

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 (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 Firpo et al (2011), letting $\hat{\Gamma}_{g,\tau}$ 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:

$$\hat{\Delta}_O^\tau = \left(X_f - X_m\right)' \hat{\Gamma}_{m.\tau} + X_f'(\hat{\Gamma}_{f.\tau} - \hat{\Gamma}_{m.\tau}) = \Delta_X^\tau + \Delta_S^\tau \quad (9)$$

The composition or explained effect can be rewritten in terms of the contribution of each covariate:

$$\Delta_X^\tau = \sum_{k=1}^{K} \left(X_{fk} - X_{mk}\right)' \hat{\Gamma}_{mk.\tau} \quad (10)$$

And the detailed wage structure or unexplained effect is:[10]

$$\Delta_S^\tau = \sum_{k=1}^{K} X'_{fk}(\hat{\Gamma}_{fk.\tau} - \hat{\Gamma}_{mk.\tau}) \quad (11)$$

As was already mentioned, the linear specification may not hold for larger changes in the covariates, producing potential biased. To tackle this problem, Firpo et al. (2011) propose a solution that combine both reweighting and RIF-regressions methods and it will the approach adopted in this work. 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. This reweighting function is:

$$w(X) = \frac{P(female\,|X)}{P(female)} \frac{P(male)}{P(male\,|X)} \quad (12)$$

Then estimate the RIF-regression on the reweighted covariates in order to obtain the coefficients needed to compute the decomposition similar to that in equations (9), (10) and (11). However, the reweighting process derive in a slightly different version of the explained and unexplained effect, due to the fact that the counterfactual now is a reweighting version of the reference group. Specifically, as Firpo et al (2001) shown, it is possible to rewrite the explained and unexplained effect as:

$$\Delta_X^\tau = \underbrace{(X_m^C - X_m)'\,\hat{\Gamma}_{m.\tau}}_{\Delta_{X,p}^\tau} + \underbrace{X_m^C(\hat{\Gamma}_{m,\tau}^C - \hat{\Gamma}_{m.\tau})}_{\Delta_{X,e}^\tau} \quad (13)$$

$$\Delta_S^\tau = \underbrace{X'_f(\hat{\Gamma}_{f.\tau} - \hat{\Gamma}_{m,\tau}^C)}_{\Delta_{S,p}^\tau} + \underbrace{\left(X_f - X_m^C\right)'\hat{\Gamma}_{m,\tau}^C}_{\Delta_{S,e}^\tau} \quad (14)$$

Where the counterfactual components came from the reweighted RIF-regression described before. The terms $\Delta_{X,p}^\tau$ y $\Delta_{S,p}^\tau$ correspond to the "pure" explained and unexplained effect, respectively. $\Delta_{X,e}^\tau$, called the total *specification error*, corresponds to the difference between the total wage structure across the classic OB and the reweighted-regression decomposition. It is a linear projection error associated at 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, $\Delta_{S,e}^\tau$ is the total *reweighting error* and represent the difference between the total explained across the two decompositions.

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

4. Results

4.1 Gender wage gap

First, we present an analysis based on OLS estimations with pool data from 2008 to 2018 (Table 4). The results show that on average woman physicians earn less money than men by position in the private sector: raw gaps are estimated in -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 a first evidence of a wage penalty against women in the healthcare sector.

TABLE 4: RAW AND CONDITIONAL GENDER GAPS – AVERAGE 2008-2018

	Log Monthly Income		Log Hourly Income	
	Without controls	With controls	Without controls	With controls
Female	-0,2995***	-0.0903***	-0.1623***	-0.0552***
Age		0.0419***		0.0324***
Age2		-0.0003***		-0.0002***
Hours		0.0049***		
Surgical act		0.0272***		
Non-surgical act		0.0003***		0
CAD		0.7107***		0.1629***
Specialty		Yes	Yes	Yes
Institution		Yes		Yes
Rel. Inst		Yes		Yes
Cons	11.13***	9.5420***	7,331***	6.1690***

Notes: N=525,896. OLS estimations with pool data from 2008 to 2018. Robust standard errors.
(*) p value < 0.1, (**) p value < 0.05, (***) p value < 0.005
Source: SCARH

Then, we present estimates of the gross gap and the conditional gap of the logarithm of medical earnings by gender by year. On average, female positions have lower earnings: 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 showed a decrease, although less than that of male physicians. These results can be seen in Tables A.5 and A.6 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, partly due to women working fewer hours than men, as shown by Colacce et al. (2020) for the rest of female workers. As for its temporal evolution, a very limited reduction is observed with respect to the 2008 value.

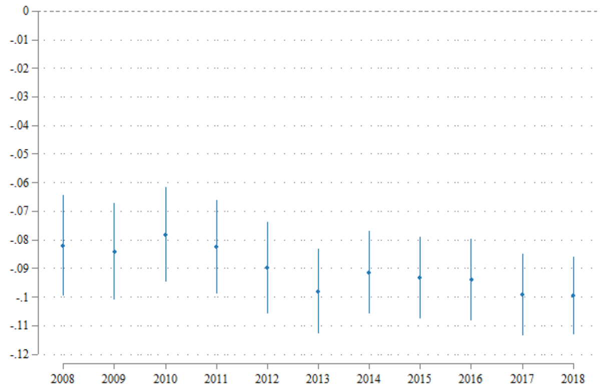
Figure 5 presents the coefficient estimates associated with the variable *Female* in equation 1, an OLS estimation with monthly wage (Panel a) and hourly wage (Panel b) as the dependent variable, controlling for individual and occupation characteristics (the regression results can be seen in Table A.7 and A.8 of the Appendix). The conditional gap is smaller than the raw gap, but the coefficient remains negative and significant at 1%. This indicates that men earn higher wages than women and that this difference is not explained by anyone of the other covariates included in the model. For monthly wage 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 observe de hourly wage, the coefficient of the binary variable *Female* is also negative, but lower than that estimated for monthly wage. In 2018, positions held by female physicians received on average an hourly income 5% lower than positions held by male physicians, given the characteristics of the position and the individuals holding it. This value is very similar to that estimated in 2008, so the conditional hourly gap remains relatively stable over the ten years analyzed.

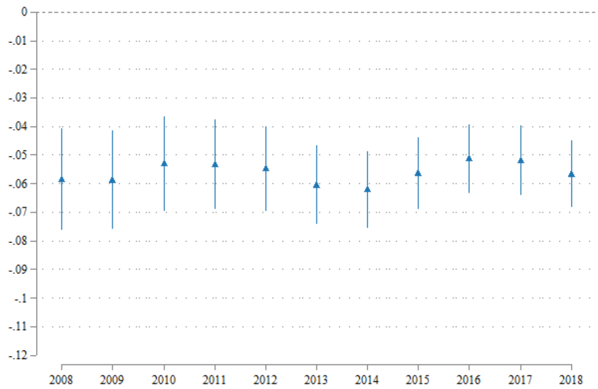
The estimated hourly earnings gap for physicians is significantly smaller than that found by Espino et al. (2014) for the labor force as a whole, whose estimate for 2011 was -25%. The difference in earnings attributed to the sex of the individual for medical positions also turned out to be smaller than the estimate of Espino et al. (2014) for workers with tertiary education, which is -14 % in 2011. The authors argue that the difference in the coefficients comparing total wage earners with the most educated can be attributed to the fact that for tertiary educated wage earners there are objective forms of certification of specific skills and knowledge that are usually a requirement at the time of hiring and a basis for wage setting. The same comment can be addressed to physicians, who are among the most highly educated of the tertiary-educated workers.

FIGURE 5: CONDITIONAL GENDER WAGE GAP.

Panel a) Log monthly salary



Panel b) Hourly salary



Notes: The dots report coefficients of the binary variable *Female* in a OLS regression, with their confidence intervals (vertical lines). The especifications 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 specialty, fixed effects by institution. *Source*: SCARH.

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 (controlling for age, region and education). However, Colacce et al. (2020) find a similar gap result for formal workers, which is around -5 % in 2018. Finally, our results are similar to that find it for Magnusson (2016) for Swedish physicians.

4.2 Gender Segregation

Horizontal segregation

Measuring horizontal segregation

To determine the existence of horizontal segregation, we calculate the Duncan (ID) and Karmel and Maclachlan segregation indices per each year (Table A.9.1 in the Appendix). Additionally, we present the decomposition of the variation of the ID between 2008 and 2018 (Table A.9.2 in the Appendix).

The ID calculated for the medical specialties of the IAMCs shows a reduction between 2008 and 2018. Specifically, the ID goes from 32% in 2008 to 29% in 2018, a decrease of 11%. The results are in line with works studying occupational segregation for Uruguay, which find lower segregation among highly qualified occupations. Katzkowicz and Querejeta (2012) find an ID value of 28% for skilled workers out of the total employed in 2011. This value is significantly lower than that calculated for less skilled workers, where occupational segregation is more significant, with an ID of 58%. Espino (2013) finds an ID value of 61% for the total number of salaried workers in the country in 2010. Espino et al. (2014) calculate an ID of 62% for all salaried employees in 2011 and of 37 % for the ones with more than 12 years of education. The temporal variations of the ID are composed of changes in the occupational structure of the labor force (Occupational effect) and the gender composition within occupations (Gender effect). Thus, the variation of the ID between 2008 and 2018 is 57% composed of the Sex effect and 25 % of the Occupational effect. The residual component explains the remaining 25% (Table A.9.2 in the Appendix)

In the same way, KM index indicates that 14% of medical positions would have to change specialty for the distribution of men and women by specialty to be equalized in 2018. This shows a drop of 12% with respect to the 2008 KM, a slightly larger drop than that observed in the ID. This difference is explained by the fact that the participation of women in the total number of positions increased from 48% to 57%.

Horizontal segregation and the gender wage gap

We present the results measuring the influence of horizontal segregation in the wage gap for physicians. Table 6 presents the results for the OLS regressions considering the segregation variables in the models for the years 2008 and 2018. The main difference is the way of controlling for specialty and institution. Now we include the percentage of women in the specialty and the institution as an explicative variable. This allows us to capture the effect of being in a work environment with a higher proportion of women on wages. The coefficient on the *Female* variable estimated with segregation controls in 2018 is slightly lower than above (in absolute value) for both the monthly and hourly cases. In the monthly case, the conditional gap widens slightly between 2008 and 2018, while in the hourly case it remains practically stable (with a drop of less than one percentage point).

TABLE 6: THE INFLUENCE OF HORIZONTAL SEGREGATION IN THE GENDER WAGE GAP: 2008 AND 2018

	2008		2018	
	Log. of monthly income with seg	Log. of hourly income with seg	Log. of monthly income with seg	Log. of hourly income with seg
Female	-0.0737***	-0.0573***	-0.0841***	-0.0500***
Age	0.0696***	0.0534***	0.0483***	0.0522***
Age2	-0.0005***	-0.0004***	-0.0004***	-0.0004***
Hours	0.0041***	No	0.0073***	No
Surgical Act	0.0249***	No	0.0357***	No
Non-surgical Act	0.0002***	-0.0000**	0.0014***	0.0007***
CAD	No	No	0.4262***	-0.0512***
% Woman by specialty	-0.2863***	-0.3199***	-0.2318***	-0.4722***
% Woman by institution	0.6707***	0.8838***	0.6658***	1.0111***
Montevideo	-0.4370***	-0.0699***	-0.2744***	0.0894***
Specialty	No	No	No	No
Institution	No	No	No	No
Rel. Inst	Si	Si	Si	Si
Cons	8.8446***	5.3255***	9.0380***	5.4960**

Note: (*) p value < 0.1. (**) p value < 0.05. (***) p value < 0.005. Robust standard errors.

Source: SCARH.

The results of the estimations incorporating the segregation variables for all years are presented in Tables A.10 and A.11 in Appendix. 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 labor income gap in the medical sector than for other workers with tertiary education. About the influence of female participation by institution on income, the estimated parameters show a positive sign for most years.

Decompositions of the gross gaps

Tables 7 and 8 show the results of the decomposition of the differences between the logarithm of women and men wages from the estimations of the models that include the segregation variables in 2018. In addition, Tables A.12 and A.13 in the appendix show details of the contribution of each variable for all years. The decomposition allows us to separate the gross labor income gap by obtaining the contribution of each covariate to it, following Bayard et al. (2003)[11].

Sex has a significant contribution to the monthly and hourly wage gap. The contribution of the sex variable in monthly wage increases its value between 2008 and 2018, going from 22% to 31%. In hourly wage, the contribution decreases slightly, from 34% to 32% in that period. This evolution is consistent with that of the coefficients estimated for the models that do not include the segregation variables. Age also explains a significant proportion of the gap, both in the monthly and hourly wage. The population structure of women is younger than that of men. As age approximates works experience, it is positively correlated with income and this contributes to men earning more. This point is relevant, considering that as time goes by and women get older, a relevant part of the income gap could be reduced (as long as women do not retire much earlier than men from the labor market, which could compensate at least a part of this transition).

In the decomposition for the monthly case, the variable that measures the concentration of women in the specialties has a significant contribution to the gross gap, 13% in 2018. This component shows a small decrease with respect to its 2008 estimate of 15%. On the other hand, in the decomposition with the logarithm of hourly income as a dependent variable, the concentration of women in specialties is the component with the highest significance in the gross gap. This component also shows an increasing evolution over time, from 33% in 2008 to 47% in 2018. This result suggests that horizontal segregation has an increasing importance in gender differences in labor earnings.

The difference between the monthly and hourly cases is due to the fact that in the monthly case there are other relevant variables that contribute to the gap, such as hours worked and surgical procedures performed (21% and 17% in 2018 respectively). On the other hand, the variable indicating whether the position is a substitute position shows a significant influence on the gap in the first years, which then declines to reach 4 % in 2018. Whether the position is highly dedicated has a very small influence in the monthly case, and zero in the hourly case. This result may derive from the fact that CAD positions are relatively few compared to the total number of positions and are concentrated in some specialties.

The results show that positions occupied by women in IAMCs have lower incomes than those occupied by men, whether comparing total monthly income or hourly income. The concentration of women in the specialty contributes significantly to explaining these differences. In any case,

[11] Averages are calculated for the variables used in the regressions, and the difference in these means between men and women is multiplied by the estimated coefficients to obtain the absolute contribution of each variable to the total gap.

there is still a component that cannot be explained by this variable or by any of the other variables included in the models.

TABLE 7: DECOMPOSITION OF LOG MONTHLY INCOME GROSS GAP BY SEX IN 2018.

	Women	Men	Difference	Absolute contribution	Relative contribution
Log. montly income	10.89	11.16	-0.27	-0.27	100%
Female	1	0	1	-0.08	31%
Hours	66.86	74.49	-7.63	-0.06	21%
Age	45	48	-3	-0.16	59%
Age2	2142	2474	-332.04	0.12	-44%
Surgical act	1	2	-1	-0.05	17%
Non-surgical act	67	70	-3	0.00	2%
CAD	0.07	0.05	0.06	0.01	-2%
% Woman by specialty.	0.63	0.48	0.15	-0.04	13%
% Woman by institution	0.57	0.56	0.01	0.01	-2%
Montevideo	0.67	0.65	0.02	-0.01	2%
Substitutes	0.22	0.18	0.04	-0.01	4%
Permanent Substitutes	0.22	0.18	0.04	-0.01	3%
Self-employed	0.12	0.14	-0.02	0.01	-3%

Note: Decomposition according to Bayard et al. (2003).

Source: own elaboration based on SCARH.

TABLE 8: DECOMPOSITION OF LOG HOURLY INCOME GROSS GAP BY SEX IN 2018.

	Women	Men	Difference	Absolute contribution	Relative contribution
Log. hourly income	7.22	7.38	-0.16	-0.16	100%
Female	1	0	1	-0.05	32%
Hours	45	48	-3	-0.17	111%
Age	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%

Note: Decomposition according to Bayard et al. (2003).

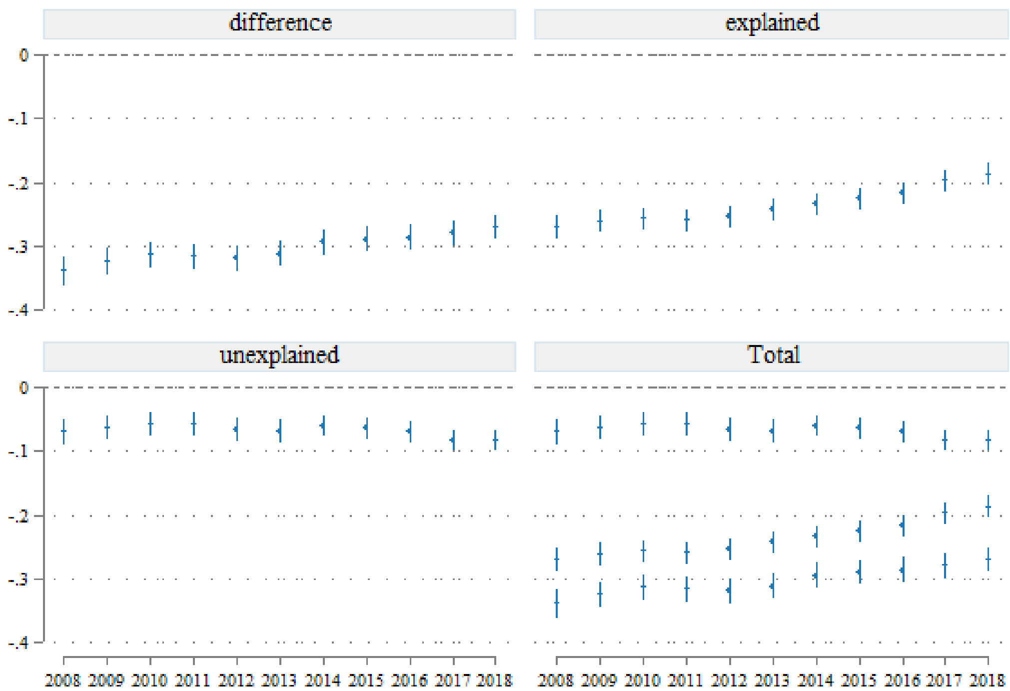
Source: own elaboration based on SCARH.

Separate regressions were also estimated between males and females to compute an Oaxaca-Blinder decomposition. We separate the difference in income from the models that include the segregation variables into an effect associated with observable characteristics (composition effect) and an effect associated with the differential returns by sex to those characteristics (structure effect). The results of these estimations are presented in Tables A.14 and A.15 of the appendix[12]. In the monthly case, we obtain that 70% of the gap is explained by the composition effect and 30% by the structure effect in 2018. The unexplained part of the gap, i.e., the structure effect, had an increasing share in the explanation of the gap.

When we consider the hourly wage, the observable characteristics, including segregation, explain 83% of the labor income gap between men and women. *Specialty segregation* is one of the variables with the greatest influence on the explained part of the gap. This suggests that horizontal segregation does indeed affect gender differences in labor income, but that a percentage of the gap remains unexplained. Consistent with the previous results, the proportion of the structure effect remained relatively stable in the hourly case.

FIGURE 6: OAXACA-BLINDER DECOMPOSITION BY YEAR

PANEL A) MONTHLY WAGE



[12] The male coefficients are taken as the non-discriminatory salary structure to construct the counterfactual.

PANEL B) HOURLY WAGE

Source: SCARH.

Finally, an alternative decomposition accounting for the role of particular medical specialties or group of them is realized. The results for monthly and hourly income are presented in Table A.16 and Figure A.1. In general, the decomposition shows the same patterns that where mentioned before, with the explained effect driving the gender gap evolution. However, it is interesting to pointing out that, as can be seen in Table A.16, specialties related to Aesthetic and Surgical Specialties play a central role in the compositions effect. This is directly in line with previous results and confirms that certain areas of medicine have historically been a place reserved for men.

Vertical segregation

The previous results suggest that there is a difference between male and female wages that is solely attributable to the gender of individuals. These results were estimated for the average wage and now we observe the differences across the wages distribution and test the glass ceiling hypothesis. For that we estimate quantile regressions using RIF functions (as Firpo et al.. 2009).

Figures 7 and 8 suggest the existence of a gender gap throughout the wage distribution. The estimated coefficients at the different points of the wage distribution are negative and significant in all years considered (2008, 2013 and 2018). However, higher coefficients are observed in the right tail of the wage distribution. This means that the wage gap widens for higher wages. showing evidence of the presence of a glass ceiling (The results of the coefficients for the variable *Female* can be seen in Table A.17 and A.18 in Appendix for 2008, 2013 and 2018). Furthermore. in Table A.18. a slight increase in this difference can be seen between 2008 and 2018. indicating that the differences do not narrow over time. Tables A.19 and A.20 detail the coefficients of some controls for 2008 and 2018.

FIGURE 7: UNCONDITIONAL QUANTILE REGRESSION COEFFICIENTS BY YEAR: MONTHLY WAGE

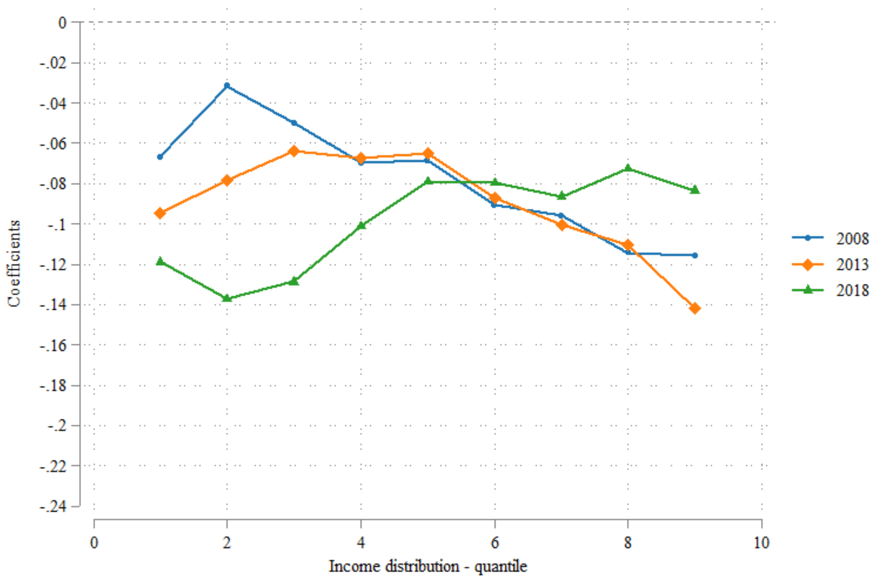
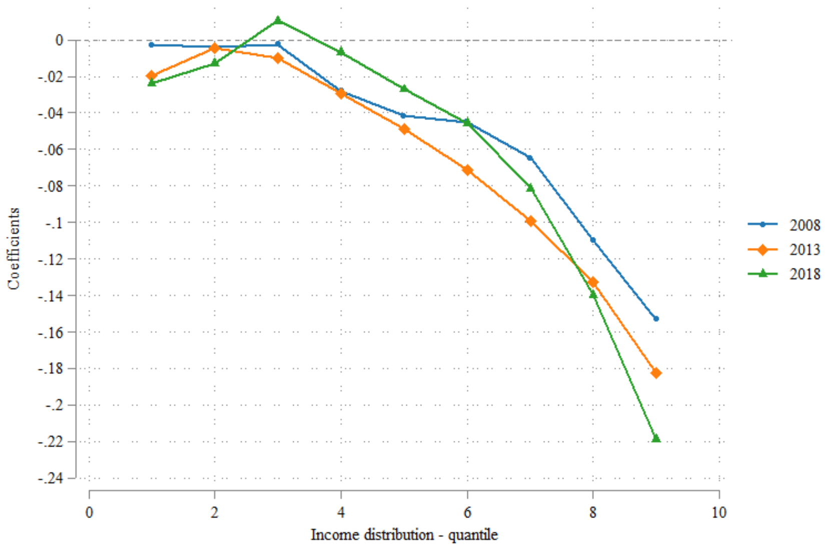


FIGURE 8: UNCONDITIONAL QUANTILE REGRESSION COEFFICIENTS BY YEAR: HOURLY WAGE



Note: For monthly salary all coefficients are statistically significant at 1%, with the exception of the first two quantiles in 2008. For hourly salary the coefficients are significant at 1 % starting at sat Q50

Source: SCARH.

5. Conclusion

In this paper, we set out to study the labor 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 earnings gap among physicians, even after controlling for observable position characteristics such as medical specialty. This suggests that the remaining difference in earnings is associated with a discriminatory factor. Specifically, in 2018, female positions in IAMCs (Collective Medical Assistance Institutions) have on average 5% lower hourly earnings than male positions, given the characteristics of the position and the person in the position. The conditional gap is lower than that found by previous studies for Uruguayan workers as a whole (Espino et al., 2014; Colacce et al., 2020), but remains virtually stable between 2008 and 2018.

We also sought to determine whether there is segregation by specialty. We found that there is segregation, measured through Duncan's and Karmel and Maclachlan's indices. In 2018, 28% of women's positions would have to change specialty to achieve an equal distribution by gender. A drop in the segregation index was observed in the period under analysis, which was explained to a greater extent by a change in the gender composition of occupations (50%) and to a lesser extent by changes in the occupational structure (25%).

Regarding the contribution of occupational segregation to the unadjusted earnings gap, we estimated regressions and decompositions of the gap following the methodology of Bayard et al. (2003) The hourly earnings gap decomposition shows that segregation by specialty 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 sex of the individual explains 32% of the difference. In addition, decompositions were performed with estimates from sex-separated regressions. In this case, it was also observed that segregation by specialty is the variable with the greatest influence on the 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 analyzed the differences in salary income beyond the mean, thanks to the estimation of quantitative regressions using the RIF method (Firpo et al., 2009). The results show that in the case of hourly income, there is 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 at 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, also known as the "glass ceiling", may be contributing to the gender income gap in the healthcare sector in Uruguay.

In summary, this study contributes to a vast literature that deals with the study of gender wage gaps in the labor market, specifically in the healthcare sector. Our findings indicate that there is a gender earnings gap among physicians in Uruguay, and that this gap is partly explained by segregation by specialty and the presence of a glass ceiling for female medical workers. The results of this study provide valuable information for policymakers to guide the design of instruments that can correct gender inequality in the workforce. This is especially important as labor income is the main source of income for most population 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.

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Appendix A: Tables and Figures

TABLE A.1: QUOTAS FOR RESIDENCIES IN 2015.

Specialty	Quotas
Health Services Administration	5
Health Services	3
Pathological Anatomy	15
Anesthesiology	9
Cardiology	13
General Surgery	3
Plastic Surgery	1
Vascular Surgery	4
Dermatology	1
Endocrinology	1
Epidemiology	4
Physiatry	2
Gastroenterology	4
Geriatrics	26
Gynecotocology	2
Hematology	10
Imaging	1
Infectology	4
Clinical Laboratory	29
Family and Community Medicine	23
Intensive Care Medicine	39
Internal Medicine	1
Legal Medicine	1
Nuclear Medicine	1
Transfusion Medicine	1
Microbiology	5
Nephrology	1
Pneumology	5
Neurology	6
Ophthalmology	4
Medical Oncology	2
Radiation Oncology	2
Otorhinolaryngology	1
Parasitology	42
Pediatrics	4
Psychiatry	1
Rheumatology	1
Occupational Health	3
Toxicology	8
Traumatology	6

Grand total	294

Source: Contreras y Faggeti (2016)

TABLE A.2: QUOTAS FOR POSTGRADUATE MEDICAL SPECIALIZATION

Specialty	Quotas
Allergology	4
Pathological Anatomy	7
Cardiology	22
Dermatology	8
Endocrinology and Metabolism	8
Pharmacology And Therapeutics	3
Gastroenterology	10
Geriatrics	13
Hematology	No limit
Imaging	14
Clinical Pathology Laboratory	15
Sports Medicine	5
Family and Community Medicine	No Limit
Intensive Care Medicine	40
Legal Medicine	6
Nuclear Medicine	6
Microbiology	8
Pneumology	10
Ophthalmology	10
Medical Oncology	10
Radiation Oncology	6
Internal Medicine	No Limit
Nephrology	15
Neurology	6
Infectious Diseases	4
Health Services Administration	No Limit
Epidemiology	No Limit
Otorhinolaryngology	6
Medical Parasitology and Mycology	No Limit
Pediatrics	40
Psychiatry	No Limit
Pediatric Psychiatry	12
Rehabilitation and Physical Medicine	6
Rheumatology	10
Occupational Health	No Limit
Transfusion Therapy and Medicine	10
Clinical Toxicology	No Limit

Source: Contreras y Faggeti (2016)

TABLE A.3: MULTI-EMPLOYMENT OF MEDICAL WORK IN IAMCS IN 2008.

Number of positions	All		Women		Men	
	Physicians	%	Physicians	%	Physicians	%
1	3,338	49%	1,822	50%	1,516	46%
2	1,875	28%	956	26%	919	28%
3	898	13%	446	13%	452	14%
4	392	6%	163	6%	229	7%
5	161	2%	62	3%	99	3%
6	68	1%	22	1%	46	1%
7 and	37	1%	6	1%	31	1%
Total	6,769	100%	3,477	100%	3,292	100%

Source: SCARH.

TABLE 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 Medicine	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 Care Medicine	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 charges	49,620	50,186	50,390	51,557	53,620	54,403
% CAD	0%	1%	3%	4%	5%	6%

Source: SCARH.

TABLE A.5: DESCRIPTIVE STATISTICS FOR AVERAGE FEMALE POSITIONS 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.

TABLE A.6: DESCRIPTIVE STATISTICS FOR AVERAGE MALE POSITIONS 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.

TABLE A.7: COEFFICIENTS FROM MODEL 1: OLS REGRESSION OF LOG MONTHLY INCOME.

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

Note: The model refers to equation 4.1. A dummy variable indicating whether the worker is permanent, substitute or independent, fixed effects by specialty and fixed effects by institution are included as additional controls. (*) p value < 0.1. (**) p value < 0.05. (***) p value < 0.005. Robust standard errors. *Source:* SCARH.

TABLE A.8: COEFFICIENTS FROM MODEL 2: OLS REGRESSION OF LOG HOURLY INCOME.

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

Note: The model refers to equation 4.1. A dummy variable indicating whether the worker is permanent, substitute or independent, fixed effects by specialty and fixed effects by institution are included as additional controls. (*) p value < 0.1. (**) p value < 0.05. (***) p value < 0.005. Robust standard errors. *Source:* SCARH.

TABLE A.9.1: DUNCAN'S AND KARMEL AND MACLACHLAN'S INDICES

Year	ID			KM		
	Index	Confidence intervals 95%.		Index	Confidence intervals al 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

Note: Confidence intervals calculated using Bootstrap (500 repetitions).

Source: SCARH.

TABLE A.9.2: DECOMPOSITION OF ID EFFECTS.

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

Source: SCARH.

TABLE A.10: COEFFICIENTS FROM MODEL 3: OLS REGRESSION OF LOG MONTHLY INCOME.

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Female	-0.074***	-0.077***	-0.069***	-0.072***	-0.079***	-0.082***	-0.072***	-0.074***	-0.074***	-0.081***	-0.084***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Age	0.004***	0.004***	0.004***	0.005***	0.005***	0.005***	0.005***	0.006***	0.006***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age2	0.070***	0.058***	0.060***	0.061***	0.064***	0.056***	0.048***	0.043***	0.045***	0.056***	0.048***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Hours	-0.001***	-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)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Surgical act	0.025***	0.027***	0.027***	0.029***	0.029***	0.028***	0.028***	0.032***	0.030***	0.039***	0.036***
	(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***	0.001***	0.001***	0.001***	0.001***	0.001***	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	0.786***	0.648***	0.613***	0.545***	0.542***	0.426***
						(0.050)	(0.022)	(0.015)	(0.015)	(0.018)	(0.019)
% Woman by specialty	-0.286***	-0.249***	-0.239***	-0.192***	-0.165***	-0.204***	-0.256***	-0.255***	-0.251***	-0.218***	-0.232***
	(0.025)	(0.025)	(0.024)	(0.025)	(0.024)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
% Woman by institution.	0.671***	0.820***	0.596***	0.356***	-0.334***	-0.379***	0.086	0.215***	0.029	0.194***	0.666***
	(0.073)	(0.080)	(0.078)	(0.073)	(0.072)	(0.074)	(0.074)	(0.072)	(0.070)	(0.070)	(0.071)
Montevideo	-0.437***	-0.488***	-0.491***	-0.467***	-0.443***	-0.380***	-0.389***	-0.364***	-0.332***	-0.325***	-0.274***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Cons	8.845***	9.057***	9.123***	9.254***	9.515***	9.715***	9.644***	9.549***	9.591***	9.184***	9.038***
	(0.096)	(0.089)	(0.084)	(0.082)	(0.080)	(0.082)	(0.082)	(0.079)	(0.079)	(0.083)	(0.081)
Obs.	36,398	42,302	44,373	45,171	47,876	49,620	50,186	50,390	51,557	53,620	54,403
R2	0.45	0.44	0.43	0.44	0.45	0.47	0.49	0.53	0.52	0.52	0.54

Note: The model refers to equation 4.6. A dummy variable indicating whether the worker is permanent, substitute or independent is included an additional control. (*) p value < 0.1. (**) p value < 0.05. (***) p value < 0.005. Robust standard errors. *Source:* SCARH.

TABLE A.11: COEFFICIENTS FROM MODEL 4: OLS REGRESSION OF LOG HOURLY INCOME.

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)
% Woman by specialty	-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)
% Woman by institution.	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	0.10

Note: The model refers to equation 4.6. A dummy variable indicating whether the worker is permanent, substitute or independent is included as an additional control. (*) p value < 0.1. (**) p value < 0.05. (***) p value < 0.005. Robust standard errors. *Source:* SCARH.

TABLE A.12: DECOMPOSITION OF LOG MONTHLY INCOME GROSS GAP BY SEX. RELATIVE CONTRIBUTION.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Female	22%	24%	22%	23%	25%	26%	24%	25%	26%	29%	31%
Age	15%	16%	17%	17%	18%	17%	18%	19%	21%	19%	21%
Age2	68%	61%	70%	73%	75%	65%	60%	52%	56%	68%	59%
Hours	-51%	-44%	-53%	-55%	-59%	-50%	-45%	-36%	-40%	-51%	-44%
Surgical Act	10%	11%	12%	13%	14%	13%	14%	15%	15%	18%	17%
Non-surgical Act	1%	1%	0%	0%	1%	4%	3%	2%	2%	0%	2%
CAD	0%	0%	0%	0%	0%	0%	-1%	-3%	-2%	-3%	-2%
% Woman by specialty	15%	13%	13%	10%	8%	11%	14%	14%	14%	12%	13%
% Woman by institution	-3%	-3%	-2%	-1%	1%	1%	0%	-1%	0%	-1%	-2%
Montevideo	3%	4%	4%	4%	3%	4%	3%	3%	3%	3%	2%
Substitute	14%	14%	15%	13%	10%	8%	7%	7%	6%	5%	4%
Regular substitutes	3%	4%	3%	4%	5%	4%	4%	3%	4%	3%	3%
Independient	2%	0%	0%	0%	-2%	-2%	-1%	-2%	-3%	-3%	-3%
Total gross income gap	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Total gross income gap in logarithms	-0.3400	-0.3257	-0.3150	-0.3167	-0.3205	-0.3125	-0.2953	-0.2906	-0.2873	-0.2806	-0.2707

Note: Decomposition following Bayard et al. (2003). *Source:* SCARH.

TABLE A.13: DECOMPOSITION OF LOG HOURLY INCOME GROSS GAP BY SEX. 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

Note: Decomposition following Bayard et al. (2003). *Source:* SCARH.

TABLE A.14: DECOMPOSITION OF LOG MONTHLY INCOME WITH SEPARATE ESTIMATES FOR WOMEN AND MEN

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Women	10.801***	10.750***	10.740***	10.792***	10.791***	10.836***	10.856***	10.875***	10.883***	10.886***	10.889***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Men	11.141***	11.076***	11.055***	11.108***	11.111***	11.148***	11.151***	11.166***	11.170***	11.167***	11.160***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Difference	-0.340***	-0.326***	-0.315***	-0.317***	-0.321***	-0.312***	-0.295***	-0.291***	-0.287***	-0.281***	-0.271***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Explained	-0.270***	-0.262***	-0.257***	-0.260***	-0.255***	-0.243***	-0.235***	-0.226***	-0.217***	-0.198***	-0.188***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Unexplained	-0.070***	-0.063***	-0.058***	-0.057***	-0.066***	-0.069***	-0.061***	-0.064***	-0.070***	-0.083***	-0.083***
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Explained effects attributable to:											
Age	-0.228***	-0.221***	-0.247***	-0.225***	-0.248***	-0.198***	-0.167***	-0.145***	-0.142***	-0.161***	-0.167***
	(0.018)	(0.017)	(0.018)	(0.017)	(0.017)	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)
Age2	0.169***	0.162***	0.189***	0.161***	0.187***	0.145***	0.117***	0.092***	0.092***	0.112***	0.122***
	(0.017)	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)
Hours	-0.046***	-0.046***	-0.048***	-0.048***	-0.051***	-0.044***	-0.047***	-0.049***	-0.053***	-0.047***	-0.050***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Surgical act	-0.032***	-0.034***	-0.034***	-0.038***	-0.044***	-0.037***	-0.038***	-0.042***	-0.042***	-0.051***	-0.043***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Non-surgical act	-0.002***	-0.001**	-0.001**	-0.001*	-0.002*	-0.011***	-0.008***	-0.006***	-0.005***	-0.001	-0.004**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
% Woman by specialty	-0.056***	-0.052***	-0.046***	-0.040***	-0.035***	-0.046***	-0.054***	-0.049***	-0.042***	-0.035***	-0.041***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
% Women by institution	0.008***	0.006***	0.003**	0.001	-0.005***	-0.005***	0.000	0.002	-0.001	0.003**	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Montevideo	-0.006***	-0.007***	-0.006***	-0.006***	-0.005***	-0.006***	-0.005***	-0.005***	-0.006***	-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)
Rest of the country	-0.006***	-0.007***	-0.006***	-0.006***	-0.005***	-0.006***	-0.005***	-0.005***	-0.006***	-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)
Permanent	-0.050***	-0.045***	-0.044***	-0.045***	-0.042***	-0.036***	-0.030***	-0.024***	-0.022***	-0.017***	-0.015***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Substitute	-0.022***	-0.020***	-0.020***	-0.014***	-0.009***	-0.007***	-0.007***	-0.006***	-0.005***	-0.004***	-0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Regular Substitute	0.002***	0.002***	0.003***	0.003***	0.003***	0.004***	0.003***	0.002***	0.001**	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Independent	-0.002***	-0.000	-0.000	-0.000	0.003***	0.004***	0.001	0.002***	0.004***	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)
CAD						0.001**	0.005***	0.008***	0.006***	0.007***	0.007***
						(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Unexplained effects attributable to:											
Age	0.046	-0.525*	-0.380	0.679**	0.257	0.563*	0.523*	0.486*	0.755***	0.845***	0.006
	(0.359)	(0.318)	(0.302)	(0.295)	(0.285)	(0.294)	(0.279)	(0.277)	(0.275)	(0.283)	(0.278)
Age2	-0.041	0.194	0.098	-0.454***	-0.252*	-0.394***	-0.318**	-0.305**	-0.439***	-0.426***	-0.069
	(0.178)	(0.159)	(0.152)	(0.148)	(0.142)	(0.144)	(0.139)	(0.139)	(0.137)	(0.139)	(0.136)
Hours	0.058***	0.063***	0.070***	0.079***	0.098***	0.106***	0.105***	0.087***	0.098***	0.119***	0.105***
	(0.013)	(0.013)	(0.012)	(0.013)	(0.015)	(0.017)	(0.017)	(0.013)	(0.014)	(0.018)	(0.017)
Surgical act	0.011***	0.012***	0.012***	0.006	-0.000	0.011**	0.007	0.006	0.000	-0.002	0.007*
	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Non-surgical act	0.024**	0.009	0.006	0.002	0.024**	0.024	0.019	0.012	0.013	-0.058***	0.033
	(0.009)	(0.009)	(0.004)	(0.003)	(0.010)	(0.028)	(0.016)	(0.009)	(0.014)	(0.020)	(0.024)
% Woman by specialty	0.062**	0.092***	0.062**	0.079***	0.081***	0.123***	0.124***	0.085***	0.034	0.014	0.063**
	(0.028)	(0.027)	(0.027)	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)	(0.031)	(0.029)
% Women by institution	0.101	0.327***	0.384***	0.340***	0.099	0.074	0.040	0.075	0.108	-0.068	-0.093
	(0.072)	(0.081)	(0.080)	(0.076)	(0.076)	(0.079)	(0.080)	(0.079)	(0.078)	(0.078)	(0.081)
Montevideo	-0.011***	-0.012***	-0.012***	-0.009***	-0.014***	-0.013***	-0.013***	-0.012***	-0.012***	-0.009***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Rest of the country	0.024***	0.028***	0.029***	0.020***	0.031***	0.028***	0.027***	0.023***	0.025***	0.018***	0.030***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Permanent	-0.026***	-0.023***	-0.026***	-0.017**	-0.024***	-0.024***	-0.024***	-0.009	-0.014**	-0.011*	-0.014**
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Substitute	0.012**	0.013***	0.005	0.012***	0.010**	0.016***	0.023***	0.013***	0.008**	0.006*	0.010***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Regular Substitute	-0.001	-0.002	0.002	-0.007**	-0.006*	-0.012***	-0.004	0.002	-0.004	-0.000	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Independent	0.000	0.001	0.003	0.003	0.005**	0.004*	-0.004*	-0.005**	0.003	-0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CAD						-0.001***	-0.003***	-0.002*	-0.001	0.001	-0.005*
						(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Cons	-0.331*	-0.240	-0.308*	-0.790***	-0.373**	-0.575***	-0.563***	-0.522***	-0.642***	-0.513***	-0.138
	(0.198)	(0.182)	(0.173)	(0.167)	(0.162)	(0.172)	(0.165)	(0.160)	(0.160)	(0.166)	(0.164)
Obs.	36,398	42,302	44,373	45,171	47,876	49,620	50,186	50,390	51,557	53,620	54,403

Note: Traditional Oaxaca-Blinder decomposition. Source*:* SCARH.

TABLE A.15: DECOMPOSITION OF LOG HOURLY INCOME WITH SEPARATE ESTIMATES FOR WOMEN AND MEN

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:											
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 by 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 by 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:											
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 by 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 by 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

Note: Traditional Oaxaca-Blinder decomposition. *Source:* SCARH.

TABLE A.16: DECOMPOSITION OF LOG MONTHLY INCOME INCLUDING GROUP OF PHYSICIAN SPECIALTIES – SELECTED COEFFICIENTS – 2008 AND 2018

	Log Monthly Income		Log Hourly Income	
Variable	2008	2018	2008	2018
Overall:				
Women	108.056	108.936	71.305	72.348
	(0.0080)	(0.0064)	(0.0064)	(0.0040)
Men	111.476	111.693	73.119	74.155
	(0.0078)	(0.0075)	(0.0069)	(0.0055)
Difference	-0.3420	-0.2757	-0.1813	-0.1807
	(0.0112)	(0.0099)	(0.0094)	(0.0068)
Explained	-0.2442	-0.1686	-0.1331	-0.1186
	(0.0091)	(0.0082)	(0.0070)	(0.0050)
Unexplained	-0.0977	-0.1071	-0.0483	-0.0621
	(0.0096)	(0.0075)	(0.0099)	(0.0066)
Explained effects attributable to:				
Age	-0.2233	-0.1690	-0.0893	-0.0746
	(0.0179)	(0.0166)	(0.0187)	(0.0146)
Age2	0.1690	0.1272	0.0305	0.0390
	(0.0172)	(0.0160)	(0.0186)	(0.0149)
Hours	-0.0429	-0.0427		
	(0.0038)	(0.0041)		
Surgical act	-0.0311	-0.0416		
	(0.0034)	(0.0047)		
Non-surgical act	-0.0022	-0.0036	0.0020	-0.0012
	(0.0007)	(0.0018)	(0.0004)	(0.0006)
General Medicine	-0.0037	-0.0081	0.0008	-0.0014
	(0.0006)	(0.0009)	(0.0004)	(0.0006)
Directors & Chiefs	0.0013	-0.0012	0.0010	-0.0012
	(0.0010)	(0.0005)	(0.0007)	(0.0004)
Pediatrics & Family Medicine	-0.0273	-0.0081	-0.0102	0.0028
	(0.0031)	(0.0026)	(0.0034)	(0.0021)
Aesthetic and Surgical Specialties	0.0139	-0.0079	-0.0829	-0.1065
	(0.0039)	(0.0051)	(0.0039)	(0.0032)
Medical Specialties	-0.0231	-0.0066	0.0204	0.0230
	(0.0021)	(0.0018)	(0.0022)	(0.0016)
ICU & Internal Medicine	0.0012	0.0017	-0.0011	0.0003
	(0.0004)	(0.0005)	(0.0004)	(0.0002)
Pathologists & Radiologists	0.0001	0.0025	-0.0011	0.0046
	(0.0004)	(0.0005)	(0.0005)	(0.0007)
Residents	0.0000	-0.0024	0.0000	-0.0044
	(0.0000)	(0.0004)	(0.0000)	(0.0007)
Unexplained effects attributable to:				
Age	-0.2592	-0.1094	1.1614	0.1291
	(0.3617)	(0.2781)	(0.3878)	(0.2474)
Age2	0.0899	-0.0381	-0.6849	-0.1155

	(0.1779)	(0.1336)	(0.1933)	(0.1229)
Hours	0.0415	0.0976		
	(0.0123)	(0.0180)		
Surgical act	0.0098	0.0076		
	(0.0041)	(0.0046)		
Non-surgical act	0.0287	0.0367	0.0064	0.0212
	(0.0098)	(0.0294)	(0.0041)	(0.0108)
General Medicine	-0.0016	0.0007	-0.0001	0.0005
	(0.0006)	(0.0007)	(0.0006)	(0.0006)
Directors & Chiefs	0.0194	-0.0016	0.0075	0.0006
	(0.0064)	(0.0066)	(0.0066)	(0.0046)
Pediatrics & Family Medicine	0.0162	0.0057	-0.0001	-0.0052
	(0.0053)	(0.0040)	(0.0057)	(0.0032)
Aesthetic and Surgical Specialties	0.0036	-0.0113	0.0084	-0.0055
	(0.0060)	(0.0061)	(0.0053)	(0.0033)
Medical Specialties	0.0033	-0.0118	0.0093	0.0012
	(0.0074)	(0.0063)	(0.0077)	(0.0047)
ICU & Internal Medicine	0.0124	0.0083	0.0040	0.0072
	(0.0028)	(0.0027)	(0.0030)	(0.0019)
Pathologists & Radiologists	-0.0014	-0.0021	-0.0045	-0.0106
	(0.0015)	(0.0014)	(0.0017)	(0.0015)
Residents	0.0000	-0.0001	0.0000	0.0016
	(0.0000)	(0.0004)	(0.0000)	(0.0004)
_cons	-0.0992	-0.1042	-0.6105	-0.0980
	(0.1865)	(0.1433)	(0.1975)	(0.1238)
Obs.	36.647	54.868	36.647	54.868

Note: Oaxaca-Blinder decomposition including group of physician specialties, which allows to estimate the effect of similar medical specialties on the gender gap. Standard error in parenthesis. *Source:* SCARH.

TABLE A.17: COEFFICIENTS OF FEMALE FROM AN UNCONDITIONAL QUANTILE REGRESSION OF LOG MONTHLY INCOME

Quantile	2008	2013	2018
Q10	-0.0668*	-0.0945***	-0.1188***
Q20	-0.0317	-0.0786***	-0.1373***
Q30	-0.0498**	-0.0639***	-0.1286***
Q40	-0.0697***	-0.0675***	-0.1012***
Q50	-0.0684***	-0.0651***	-0.0791***
Q60	-0.0908***	-0.0873***	-0.0795***
Q70	-0.0961***	-0.1006***	-0.0863***
Q80	-0.1142***	-0.1102***	-0.0726***
Q90	-0.1156***	-0.1416***	-0.0834***

Note: Standard errors calculated with bootstrap (500 repetitions). * p value< 0.1 ; ** p value< 0.05 ; *** p value< 0.01 *Source*: SCARH.

TABLE A.18: COEFFICIENTS COEFFICIENTS OF FEMALE FROM AN UNCONDITIONAL QUANTILE REGRESSION OF LOG HOURLY INCOME

Quantile	2008	2013	2018
Q10	-0.0029	-0.0194	-0.0135
Q20	-0.0039	-0.001	-0.0104
Q30	-0.0052	-0.0065	0.0124
Q40	-0.0304**	-0.0247**	-0.0046
Q50	-0.0434***	-0.0451***	-0.0236***
Q60	-0.0486***	-0.0661***	-0.0408***
Q70	-0.0692***	-0.0901***	-0.0738***
Q80	-0.1077***	-0.1151***	-0.1254***
Q90	-0.1602***	-0.1470***	-0.1887***

Note: Standard errors calculated with bootstrap (500 repetitions). * p value< 0.1 ; ** p value< 0.05 ; *** p value< 0.01 *Source*: SCARH.

TABLE A.19: COEFFICIENTS FROM AN UNCONDITIONAL QUANTILE REGRESSION OF LOG MONTHLY INCOME

Variable	2008			2018		
	Q10	Q50	Q90	Q10	Q50	Q90
Female	-0.067**	-0.068***	-0.116***	-0.119***	-0.079***	-0.083***
	(0.029)	(0.014)	(0.012)	(0.020)	(0.011)	(0.009)
Age	0.093***	0.077***	0.011*	0.066***	0.054***	-0.018***
	(0.012)	(0.005)	(0.006)	(0.008)	(0.004)	(0.003)
Age2	-0.001***	-0.001***	0.000	-0.001***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hours	0.004***	0.004***	0.003***	0.006***	0.008***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Surgical act	0.028***	0.022***	0.025***	0.028***	0.027***	0.036***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Non-surgical act	0.000***	0.000***	0.000***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAD				-0.375***	0.270***	0.000
				(0.029)	(0.029)	(0.000)
Cons	7.047***	8.710***	11.168***	7.733***	9.336***	12.285***
	(0.306)	(0.132)	(0.128)	(0.191)	(0.094)	(0.076)
Obs.	36,398	36,398	36,398	54,402	54,402	54,402
R2	0.17	0.37	0.27	0.18	0.45	0.34

Note. A dummy variable indicating whether the worker is permanent, substitute or independent, fixed effects by specialty and fixed effects by institution are included as additional controls. Standard errors calculated with bootstrap (500 repetitions). * p value< 0.1 ; ** p value< 0.05 ; *** p value< 0.01 *Source:* SCARH.

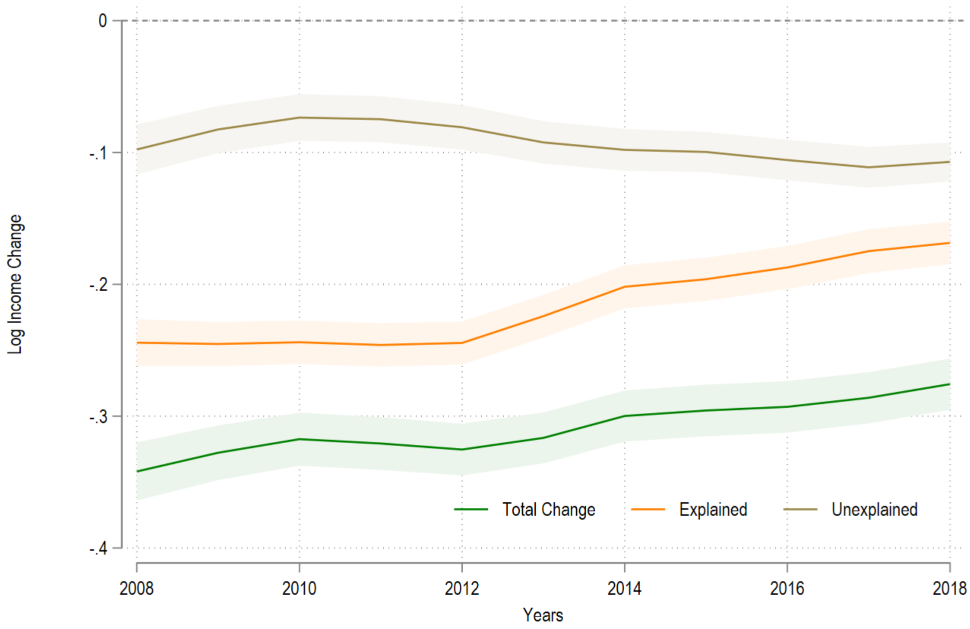
TABLE A.20 COEFFICIENTS FROM AN UNCONDITIONAL QUANTILE REGRESSION OF LOG HOURLY INCOME

Variable	Q10	Q50	Q90	Q10	Q50	Q90
Female	-0.003	-0.043***	-0.160***	-0.013*	-0.024***	-0.189***
	(0.017)	(0.011)	(0.022)	(0.008)	(0.005)	(0.015)
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)
Age2	-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				0.221***	0.178***	-0.380***
				(0.014)	(0.023)	(0.020)
Cons	3.896***	6.048***	7.692***	5.077***	6.691***	8.016***
	(0.197)	(0.098)	(0.213)	(0.091)	(0.042)	(0.142)
Obs.	36,398	36,398	36,398	54,402	54,402	54,402
R2	0.11	0.21	0.11	0.17	0.27	0.11

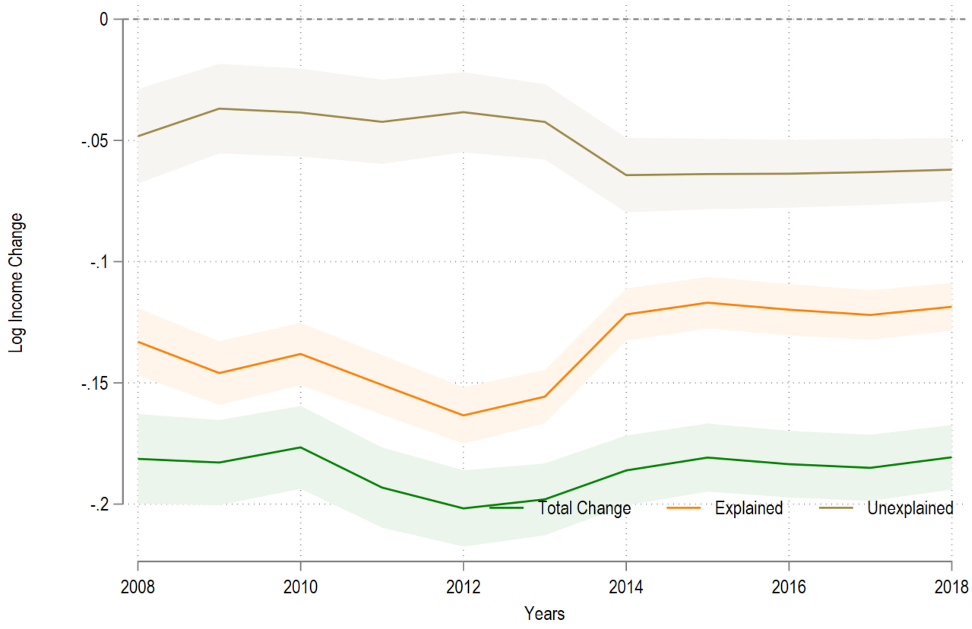
Note. A dummy variable indicating whether the worker is permanent, substitute or independent, fixed effects by specialty and fixed effects by institution are included as additional controls. Standard errors calculated with bootstrap (500 repetitions). * p value< 0.1 ; ** p value< 0.05 ; *** p value< 0.01 *Source:* SCARH.

FIGURE A.1 DECOMPOSITION OF TOTAL CHANGE INTO EXPLAINED AND UNEXPLAINED EFFECTS – INCLUDING GROUPS OF MEDICAL SPECIALTIES - 2008 TO 2018

Panel a) Monthly income



Panel b) Hourly income



Source: SCARH

Appendix B: Methodological complement

B.1 Segregation Indices

In this sections we briefly describe the two segregation indices employed to measure horizontal segregation. The first one, proposed by Duncan and Duncan (1955), was original designed to measure the degree of residential segregation by race. Applied to labor market in general, and to gender medical labor segregation by specialty in particular, the Duncan Index (DI) measures the percentage of female workforce who would have to move from one group (specialty) to another in order to have an equal distribution by sex. The index is defined by:

$$DI = \frac{1}{2}\sum_{g}\left|m_g - f_g\right|$$

Where m_g is the proportion of males working in 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 ID is its sensitivity to the level of aggregation of the groups.[13] To correct this problem, an usual alternative[14] consist of decompose 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.

$$Sexo = \frac{1}{2}\left[\sum_{p}\left|\frac{m_{p2} * T_{p1}}{\sum_p m_{p2} * T_{p1}} - \frac{f_{p2} * T_{p1}}{\sum_p f_{p2} * T_{p1}}\right| - \sum_{p}\left|\frac{m_{p1} * T_{p1}}{\sum_p m_{p1} * T_{p1}} - \frac{f_{p1} * T_{p1}}{\sum_p f_{p1} * T_{p1}}\right|\right] \quad (4.3)$$

$$Ocup = \frac{1}{2}\left[\sum_{p}\left|\frac{m_{p1} * T_{p2}}{\sum_p m_{p1} * T_{p2}} - \frac{f_{p1} * T_{p2}}{\sum_p f_{p1} * T_{p2}}\right| - \sum_{p}\left|\frac{m_{p1} * T_{p1}}{\sum_p m_{p1} * T_{p1}} - \frac{f_{p1} * T_{p1}}{\sum_p f_{p1} * T_{p1}}\right|\right] \quad (4.4)$$

[13] This means that an increase or decrease in the ID can be explained by changes in the sex 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 ID would show a decrease with no change in gender shares within specialties.

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

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

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

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

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