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Wage discrimination by gender in Mexico: The case of management and professional jobs

Discriminación salarial por género en México: el caso de los puestos profesionales y directivos

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Abstract

This is an analysis of labor market discrimination based on gender, which focuses on the top mean income occupations in Mexico: management and professional workers. We estimated the wage differential between male and female workers due to possible gender discrimination, using the sample of skilled professionals and managers from the Mexican National Survey of Occupation and Employment (ENOE) for the third quarter of 2016 and 2022. We used the Oaxaca-Blinder decomposition to estimate the income gap between male and female workers. We observed that the unexplained part of the Oaxaca-Blinder decomposition, which is usually considered economic discrimination, is mainly driven by experience (age) and to a less extend tertiary education. Another finding is that in this six-year period, the real income gap against female managers increased more than 40% while this increase was about 5% for female professionals. We also observed that other variables such as university education are more significant for female professionals than for female managers.

JEL Code: J16, J31, J71
Keywords: gender discrimination; wage differentials; wage discrimination

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Resumen

Este es un análisis de la discriminación en el mercado laboral por motivos de género, que se centra en las ocupaciones con mayores ingresos medios en México: trabajadores profesionales y directivos. Estimamos el diferencial salarial entre trabajadores y trabajadoras debido a posible discriminación por género, utilizando la muestra de profesionales calificados y directivos de la Encuesta Nacional de Ocupación y Empleo (ENOE) de México para el tercer trimestre de 2016 y 2022. Utilizamos la decomposición Oaxaca-Blinder para estimar la brecha de ingresos entre trabajadores y trabajadoras. Observamos que la parte inexplicable de la descomposición Oaxaca-Blinder, que generalmente se considera discriminación económica, está impulsada principalmente por la experiencia (edad) y, en menor medida, por la educación terciaria. Otro hallazgo es que, en este período de seis años, la brecha de ingresos reales frente a las mujeres en puestos directivos aumentó más del 40%, mientras que este incremento fue de alrededor del 5% para las mujeres profesionistas. También observamos que otras variables como la formación universitaria son más significativas para las mujeres profesionistas que para las directivas.

Código JEL: J16, J31, J71
Palabras clave: discriminación de género; diferenciales salariales; discriminación salarial

Introduction

There is a growing interest in gender discrimination in the labor market in Mexico, and several policies have been implemented in order to decrease the wage gap between male and female workers. But the reality is that female workers are still earning less than male workers in similar occupations. Although there is a consensus that wage differentials may decrease with a large well-educated female labor force and proper policies aimed to strengthen female labor market participation.

Mexico has improved in several social and economic indicators in the last decades, and now more women receive higher education and participate actively in the labor market. In 2013, about 44% of the employed workers were women and about 55% new entrances to the labor market in 2014 were also women. The rate of growth of female positions from 2008 to 2013 doubled compared to men and, in the service sector, female participation is close to be 1:1 ratio with men. More women are achieving higher education today thanks to several improvements in social policies. Mexico has still Human development indicators below the OCDE average, but thanks to economic development policies, women has achieved some improvements in the labor market.

The present work is not about female labor participation or female labor supply, but about wage differentials between male and female workers, and the analysis of factors that are driving these differences. Table 1 shows the problem in a very neat way. This table shows the hourly mean wage earned by male and female workers by groups of occupations. The group of management, professional workers and those in the crafts and trades have the larger wage differentials from other categories. Workers in the crafts and trades are mainly blue-collar workers with less than a third of the hourly wage of managers and professionals,

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which are considered white collar workers. So, our main research interest will be those workers on the top wage tiers: managers and professionals.

Table 1
Mean hourly wage by group of workers in Mexico 2016

Type	Male	Female	Total	Difference
1. Managers	97.93	86.59	93.8	11.34
2. Professionals	89.12	74.68	81.57	14.44
3. Technicians and associate professionals	46.71	46.95	46.8	-0.24
4. Clerical support workers	36.85	37.33	37.13	-0.48
5. Service and sales workers	29.8	21.71	26.03	8.09
6. Skilled agricultural, forestry and fishery workers	19.06	11.97	17.88	7.09
7. Craft and related trades workers	28.17	16.16	25.98	12.01
8. Plant and machine operators, and assemblers	30.87	24.66	29.54	6.21
9. Elementary occupations	19.04	20.55	19.61	-1.51
0. Armed forces occupations	41.31	44.79	41.5	-3.48
X. Not elsewhere classified	55.85	33.32	42.46	22.53

Data from International Labor Organization ILO using data from the Mexican National Institute of Geography and Informatics INEGI. In Mexican Pesos.

We usually identify professional workers with the term white-collar but this last concept comes from sociology rather than economics. It describes occupations of mostly clerical jobs rather than the traditional manual labor. Perhaps an influential work in this topic is the book written by Charles Mills, entitled: ”White-Collar: the American Middle Classes” Mills and Jacoby (2002); which describes the raising of new occupations in the US compared to the traditional blue-collar jobs. Currently, we understand white collar occupations as those requiring usually highly specialized knowledge, tertiary education and advanced training, enjoying a permanent position with defined office hours, a periodic payment and increased responsibilities associated to the job. On the contrary, blue-collar work is usually manual or physical effort, requiring less training, might not have permanent workplace and sometimes wages are paid by the hour. Sometimes we include in the white-collar category the executives and managers but also very specialized technicians.

In this work, we only study managerial and professional jobs as defined by the the Mexican National System of Occupations (SINCO), as shown in the two first categories in table 1. The motivation for this analysis comes from the fact that the Mexican economy is now predominantly urban and with a large service sector. For economic development, the group of managerial and professional workers are a very important part in the creation of value and therefore income. From the policy perspective, it is also important to know the variables that affect wages in these occupations, and the possible bias in terms of economic discrimination against some groups, especially women.

A standard approach to examine wage differentials was pioneered by Ronald Oaxaca Oaxaca (1973) and Alan Blinder Blinder (1973), both published in 1973. Ronald Oaxaca included this decomposition technique applied to gender discrimination in his Doctoral dissertation at Princeton University. Alan Blinder also wrote a similar paper while assistant professor at Princeton University. This decomposition technique has become very standard when studying economic discrimination and has been used widely.

The Oaxaca-Blinder decomposition is a very useful tool to observe for economic discrimination or unobserved factors and has been used widely in many empirical studies. There are some works that explain how globalization and free-trade policies have increased labor market participation of women and reduced wage gap in export-oriented firms and manufacture. For example, Villarreal et al (2007) and Aguayo-Tellez et al (2010) are analyses that study the effect of female participation in export-oriented firms and improved conditions for women. Dominguez-Villalobos et al. (2010) have an opposite result, when implementing a wage regression, they found a negative effect on female participation on wages. Mendoza-Gonzales (2020) perform a nonparametric decomposition and found that gender wage gap is higher at low-pay jobs but decreases for white collar positions.

There are other works related to gender discrimination and wage differentials in Mexico. Hazarika and Otero (2004) analyze the effect on foreign trade on gender wage differentials for urban workers and they found that trade liberalization had a positive effect in decreasing wage differentials between men and women. But, on the other hand, Artecona and Cunningham (2002) found somehow an opposite result. Navarrete (2013) is an analysis of income decomposition applied to study economic discrimination against indigenous people in Mexico. Bustamante et al. (2012) is an analysis using Oaxaca-Blinder decomposition to examine for unobserved factors that affect the access to the health system for migrant workers in US. McEwan and Marshall (2004) use this method to explain why Cuban students score higher than Mexican students. Campos-Vázquez et al. (2014) uses a variation of the Oaxaca-Blinder decomposition to analyze the effect of government transfers on inequality in Mexico.

Perhaps, a related work to this is Popli (2013), who uses Oaxaca-Blinder decomposition and a Non-parametric decomposition to analyze both formal and informal sector income. She found that the unexplained part of the gender gap is increasing in the upper tail of the distribution. Arceo-Gómez (2014) is also a study on the gender wage differentials in Mexico using, among others, the Oaxaca-Blinder decomposition. Rodriguez Pérez and Castro-Lugo (2014) is also a similar analysis of wage discrimination using Oaxaca-Blinder decomposition but applied to Mexican regions. Our work also uses the Oaxaca-Blinder decomposition applied only to Professional positions in the Mexican labor market. We also estimate the two-fold and three-fold decomposition to obtain both the explained and unexplained parts, the last one usually considered as economic discrimination.

Pagán et al (2000) uses an Oaxaca type decomposition to study female discrimination and access to labor market in rural areas of Guanajuato, Puebla and Veracruz. They mention that there are structural factors that keeps the reservation wages of women too low and recommend implementing equal-pay laws and gender-

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based quotas in the labor market. Chudnovsky et al. (2024) is an interesting study on the merit-based selection process for management jobs in the Mexican public administration. They show that the selection process does not favor women, and still reproduce gender discrimination in the public administration.

This work is organized as follows: The first part is an introduction to the analysis with a concise literature review, motivation and research objectives. The second part contains a brief theoretical background on labor market discrimination. The third is a description of the data and statistical procedures, which includes a short explanation of the Oaxaca-Blinder decomposition. The last section summarizes the main conclusions.

Theoretical background

This work deals with wage differentials between male and female workers in managerial and professional jobs, positions that are characterized of high responsibility and skills. In recent years, Mexico has improved in terms of educational attainment for women, and access to labor market opportunities. But, before we may measure current conditions of female workers, we must admit that, in some respects, these are also product of the labor market forces such as supply and demand. Rosen (1986) formalized the theory of equalizing differences from Adam Smith, giving us a theoretical tool to understand wage differences due to types of jobs, level of responsibilities, disamenities and so forth. On the other hand, Becker (1964) introduced the theory of human capital, which explains the wage gap due to differences in educational attainment, health, inherent productivity, among other individual characteristics.

Traditionally, men had higher tertiary education attainment, especially in the 25 to 64 years old group. However, in 2019, women showed a 4% higher tertiary education attainment than men for the 25 to 34 years old group. One characteristic of female workers is that university degrees may also be biased towards degrees in the humanities, management and education rather than the engineering and technology, then education may not be the only characteristic that may influence wages in top tier jobs. Gender inherent characteristics, including the level of human capital, are important but also the characteristics of jobs such as level of commitment, responsibilities and experience required.

Wage differentials between male and female workers are usually, but not limited, due to two main reasons: 1. Differences in productivity, and 2. Discrimination. The first reason may be explained by personal choices such as occupation, marriage and motherhood, and other inherent productivity. But female discrimination in the labor place means that women are unequally treated despite being equally productive. In his renown work, Becker (1957) suggested that workers belonging to a minority may be affected by prejudice from employers and coworkers. But female workers are not a minority in the labor market anymore, as female participation is about 47% in Mexico as for 2023. So, we may expect that wage differentials between male and female workers may be due, in part, to inherent group differences as well as pure discrimination.

Let us assume that a typical firm has a profit function of the type:

$$\pi = PQ - L^M w^M - L^F(\theta w^F)$$

Where P is the market price of the production Q; L^M and L^F are the labor supply of male and female workers, w^M and w^F are the wage schedules for male and female workers and θ is a parameter that describe inherent female characteristics. We assume that $0<\theta<1$, and if $\theta=1$, then, there are no differences between male and female productivity. For example, is female workers decide not to marry and not to have children, and develop same aptitudes toward similar jobs than men, then $\theta=1$.

Let us now assume that the owner or company has a utility function of the type:

$$U(\pi, wF) = \pi - \delta w^F$$

Where $\delta \geq 0$ is a coefficient of gender discrimination. If $\delta=0$, then, there is no discrimination against women and owners does not derive any disutility for paying higher wages to women. In an ideal world, we expect that $\theta=1$ and $\delta=0$, but this is evidently not true as $w^F<w^M$ continues to be a reality in the marketplace. In this work, we assume that both, inherent differences between female and male workers exists ($\theta<1$) but also there must be some kind of discrimination against female workers ($\delta<1$). Therefore, the objective is to use decomposition methods to measure and research the features which make up the wage differential between these groups of workers.

Data and methodology

The data and the selection problem

We used the micro-data from the Mexican National Occupation and Employment Survey (ENOE) for the third quarters of 2016 and 2022. We chose these two points in time where the economy is performing similarly in terms of GDP growth rates, to disregard differences in cyclical patterns. The survey is representative nationwide, with detailed information about wages, salaries, bonuses, fringe benefits, occupations, individual and employment characteristics.

The category of management workers includes all high-ranking officials in all levels of government and private corporations, all kind of managers, directors, coordinators and chiefs in NGOs, private companies, public enterprises, unions, political parties, etc. The category of professional workers includes all liberal and technical professions such as accountants, lawyers, researchers, artists, engineers in all subjects, professors and teachers, doctors, nurses and all kind of health professionals, sport people, and all support and assistants related with liberal sciences and technologies.

The occupations categories displayed in table 1 are defined by the Mexican National System for Classification of Occupations (SINCO), so we extracted from the ENOE sample those individuals working in the first and second groups: Management and professional jobs. Therefore, about 24 thousand workers were included in the analysis in these two categories.

As in many other surveys, there is a problem of missing information in labor earnings due possibly to selection bias, self-selection or non-response bias. In this case, excluding the individuals that did not declare labor earnings may cause a serious bias and the sample cannot be considered random anymore. If self-selection is to be the main problem, then people do not declare earnings because they prefer not to work until the wage rate is high enough to compensate for their reservation wage. Housewives labor supply is a clear example of self-selection. As there is missing information on the variable income from work, there must be a chance that selection is present in the data. For this reason, we decided to perform a Heckman correction to account for the missing data assuming a non-random sample.

If the data is censored or missing, the regression will not offer accurate estimates, then estimating the traditional model regression model $Y^{*}=X\beta+\varepsilon$ is not appropriate, because there are missing observations in the dependent variable. First, we assume that the pattern of missing data follows a latent process in the form:

$$D^{*}=Z\theta+\mu$$

where:

$$D=\begin{cases}1 Si D^{*}>0\\ 0 Si D^{*}\leq 0\end{cases}$$

Here D=1 if Y is not missing, which also means that $-Z\theta\leq\mu$. Because we assume that $\mu\sim N(0,1)$, we may find a correction for the model with selection using the data D=1.

$$E(Y^{*}|Y \text{ observed})=X\beta+\rho\sigma^{2}\lambda$$

Where ρ is the correlation coefficient, σ^2 is the variance and λ is the Mills's ratio. Using this model, we performed a two-step regression, first estimating labor market participation using a Probit regression with individual characteristics, family and labor market information, and later a Heckman selection-corrected model. For the first step, we estimated a Probit regression $D=Z\theta+\mu$, where D is a dummy variable that accounts for those participating in the labor market and Z is includes independent variables such as education, number of children and family income. From this Probit regression we obtained the Mills's ratio, and then performed the Heckman correction model in a separate OLS wage regression $Y^H=X\beta+\rho\sigma^2\lambda$, using Maximum Likelihood estimator. Once we obtained the estimates from the Heckman corrected model, we imputed the predicted values of labor earnings on the missing information in the entire ENOE sample.

Oaxaca-Blinder decomposition

As mentioned before, the Oaxaca-Blinder decomposition is a standard methodology created by Ronald Oaxaca in Oaxaca (1973) and Alan Blinder in Blinder (1973). This decomposition is very useful to explain the differences between two groups using linear regression techniques. In our regression analysis, we want to explain differences in labor earnings between female and male workers. Let male's labor income be $Y_i^M=\beta_{k,i}^M X_{k,i}^M+\varepsilon_i$ and female $Y_j^M=\beta_{k,j}^F X_{k,j}^F+\varepsilon_j$. Both male and female workers are explained by the same K covariates, and the vector β contains all coefficients with K−1 being the slope coefficients the regressions for each group, i=1,2,3,…,M, and j=,1,2,3,…,F. The standard assumption is that the error term is distributed normally with mean zero and variance σ^2. The decomposition starts subtracting the difference in means between these two groups:

$$\triangle \overline{Y} = \overline{Y}^M - \overline{Y}^F = \underbrace{(\overline{X}^M - \overline{X}^F)'\widehat{\beta}^F}_{\text{endowment}} + \underbrace{\overline{X}^{F'}(\widehat{\beta}^M - \widehat{\beta}^F)}_{\text{coefficients}} + \underbrace{(\overline{X}^M - \overline{X}^F)'(\widehat{\beta}^M - \widehat{\beta}^F)}_{\text{interaction}} \tag{1}$$

The first terms in the right in equation 1 is group difference in covariates, the so-called endowment effect, that considers that both groups are different because they receive more or less of something, for example formal education, opportunities, etc. The second part of 1 explains the differences in coefficients between the two groups that can be attributed to unknown factors including discrimination. And the last term which is called interaction, explains differences in both: covariates and coefficients. The above equation 1 is known as threefold decomposition, and considers we are using the low-income group (female workers) as the reference group for decomposition. Although we may use the group of male workers as the reference group for the decomposition as well:

$$\Delta \overline{Y} = (\overline{X}^M - \overline{X}^F)'\widehat{\beta}^M + \overline{X}^{M'}(\widehat{\beta}^M - \widehat{\beta}^F) + (\overline{X}^M - \overline{X}^F)'(\widehat{\beta}^M - \widehat{\beta}^F)$$

(2)

Although this decomposition might explain positive discrimination on the group of male workers when used as benchmark, because the Oaxaca-Blinder decomposition does not offer any index to be used as an anchor for comparison. Another approach might be to assume a nondiscriminatory vector β^R and rewrite the labor income gap as:

$$\Delta \overline{Y} = \underbrace{(\overline{X}^M - \overline{X}^F)'\widehat{\beta}^R}_{\text{explained}} + \underbrace{\overline{X}^{M'}(\widehat{\beta}^M - \widehat{\beta}^R) + \overline{X}^{F'}(\widehat{\beta}^R - \widehat{\beta}^F)}_{\text{unexplained}}$$

(3)

The expression in equation 3 is also known as the twofold Oaxaca-Blinder decomposition which explains differences in covariates across groups. The unexplained part is attributed to unobservable variables which also is due in part to discrimination. The decision is now which kind of non-discriminatory vector β^R must be used as index. If we say that there is solely discrimination against female workers, then $\beta^R=\beta^F$; if we say that only positive discrimination for male workers exists then $\beta^R=\beta^M$. Because there is also a real possibility that both types may exist then we may use weights for example $\beta^R = 0.5\beta^F + 0.5\beta^M$ as suggested by Reimers (1983) or a weighted average in terms of labor participation as suggested by Cotton (1988):

$$\beta^R = \frac{F}{F+M}\beta^F + \frac{M}{F+M}\beta^M$$

Another method is to use pooled regression with each sample group used independently as shown by Hlavac (2014), one without and another with the discrimination covariate. In figure 2 at the end of this paper there is an estimation of the explained and unexplained income gap using the twofold decomposition in real pesos of 2018 for the categories of managers and professional workers in Mexico, with the last two columns using decomposition between unexplained parts that favor male workers and those that do not favor female workers for each category. The two pooled regression A3 and A4 at the end of the paper and the pooled estimates in Figure 2 comes from Neumark (1988) which derived an alternative method to obtain the wage differentials without splitting the sample. The Neumark estimate is defined by:

$$\beta = (X'\Omega X)^{-1}(X\Omega A)$$

Where X is a JxK matrix of workers' characteristics, for a type or group J of workers and K regressors. The matrix $\Omega = diag(M_1+F_1,\ldots,M_J+F_J)$ and the A matrix with the jth element being:

$$A = \left[\frac{M_j}{M_j + F_j}\right]\left(ln\hat{w}_{Mj}\right) + \left[\frac{F_j}{M_j + F_j}\right]\left(ln\hat{w}_{Fj}\right)$$

Were ln ŵ's are the fitted values of the wage regressions for each gender and each worker. A total pooled regression was performed and then another one with the female covariate and, as predicted by Neumark (1988), his estimation of gender discrimination is lower than the traditionally Oaxaca with $\beta^R = \beta^M$. We use package in R developed by Hlavac (2014) to estimate the above decompositions.

Analysis

Table A2, at the end of the paper, shows the two-fold Oaxaca-Blinder decomposition using different weights and estimates in real Mexican Pesos of 2018 for both, managers and professionals. The explained coefficients are mostly negative for both categories, then there is a positive wage differential in favor of female workers in the explained part of the wage differential, although the standard deviation is relatively large, especially in the year 2016Q3 for managers. The explained part of the decomposition shows the differences in individual characteristics between male and female workers, such as education, experience, marital status, self-employment and the condition of head of the household. Differences in these covariates are making a case for women, as they are receiving a better pay than men in professional jobs. In the case of management jobs, there is also a negative differential which means that women get a better pay; however, standard deviations are large, which means that this differential is not likely different from zero. For example, the Oaxaca decomposition in the explained part for 2022Q3 is only $25.16 real pesos in favor of female managers but the standard deviation is $385.99 real pesos, which means that male and female workers are most likely to receive equal pay, given their similar individual conditions.

But the columns of interest are those of the unexplained part, which show the wage differential due to unknown factors (including gender discrimination). For example, assuming that the non-discriminatory vector is balanced by labor male participation, $\beta^R = 0.56$ for managers and $\beta^R = 0.53$ for professionals, we may see that the wage gap due to unexplained factors is positive and different for both categories. This means that there are inherent factors and discrimination against female workers in the wage gap. An example is the

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managers wage gap which was $1,063.92 real pesos in 2016Q3 and $1,521.03 for 2022Q3, which is an increase of 43% in six years. For the professionals, the income gap was only $701.33 pesos in 2016Q3 and $716.78 in 2022Q3 which is only an increase of 2%. Looking at all different weights in table 2, we confirm that the income gap against female managers is relatively worse off than for professional female workers. Although these amounts may not entirely due to gender discrimination, we can observe that the wage gap against female managers increased substantially. The columns ”unexplained M” and ”unexplained F” disaggregate the unexplained part of the wage gap into unexplained factors that favor male workers and those unexplained factors that play against female workers.

Figure A1 shows the graphs of the twofold Oaxaca-Blinder decomposition for all variables in the labor income regression for the two categories of workers. In the case of managers, the explained part of the wage gap can only be justified, though with a very small effect, by age (experience), and perhaps the condition of head of the household for the 2022Q3 sample. Something similar is true for the unexplained part of the wage gap, with the main driving factor being the variable age in the form of experience and, to a less extend, undergraduate education and head of household condition. This is also true for professional workers, as all variables has a small effect in the explained part of the wage gap and the variables age, undergraduate education and head of household condition play against female professionals.

Something similar can be seen in the threefold decomposition in figure A2. The coefficient part shows that, if there is gender discrimination, it must be attributed mainly by the covariate age for both managers and professionals. Although there are other variables that may influence the wage gap for professionals such as having a bachelor's degree or being married.

The regressions used to estimate the twofold decomposition are shown in figures A3 and A4, with mostly all covariates statistically significant for professional workers but only for some variables in the case of managers. In the pooled regression, we can observe that, for the year 2022Q3, the percentage of decrease in labor income is 7.2% for female professionals and 7.8% for female managers compared to male workers. Something important to note is that tertiary education is not statistically significant for managers compared with professionals.

Conclusions

In this work we estimated wage gap between male and female workers for two broad categories: management and professional jobs. We concluded that the main factor behind economic discrimination against female workers is mainly due to work experience (age), although tertiary education at the undergraduate level is important but much less than expected. The conditions behind experience (age), as the most important factor in explaining labor market discrimination against women, are not clear at all. The causes may be several, such

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as the possible lack of access to fair opportunities, job networking, lack of certification of abilities, maternity leave, among other reasons. Therefore, further research is needed. Some of these causes may be strongly influenced by the institutional framework such as the labor laws, unions, contracts, seniority clauses, social security, etc.

Although the endowment part of the Oaxaca-Blinder decomposition is not quite significant for managers, the unexplained part reflects experience (age) is more important for explaining possible gender discrimination. In our sample, female labor participation is 44% for managers while is 47% for professionals, and we expect that parity may be achieve in the next years. But we still can see that the wage gap between female and male workers is increasing in these categories. In the six-year period, the real income gap has increased substantially for managers, sometimes as much as 40%. Although for professional workers the increase is small, it is still a concern. Our work supports Popli (2013) findings, that the unexplained part of the wage gap is increasing in the upper tail of the earnings distribution.

We observe that the unexplained part is sometimes twice as large for managers than professionals. This may be an indication that female workers are not getting to top tier positions with a higher degree of responsibility and pay. It is possible that discrimination is one of the reasons why female workers are excluded from top tier positions in the management jobs, though other causes must be explored.

In this paper, we observe that explained part of the wage gap positively favor female workers while the unexplained part, which may account for discrimination, is still larger and cannot offset the advantage women have in their endowments. Furthermore, depending in the type of weights, the unexplained part of the wage differential is about twice as large for manager than those for professional women. This may also support the findings of Chudnovsky et al. (2024). For female managers, the wage gap due to possible discrimination ranges from $910 to $2000 real pesos for the year 2022Q3, and $544 to $753 real pesos for professional women in the same year. Only for professional jobs, we may observe some offset due to endowments such as tertiary education mainly. Professional occupations play an important role in modern economies and may have been favored by trade liberalization and free market policies as well as a better educated workforce.

There is a broad discussion and policy recommendations among research, some advocating for gender quotas, equal-pay legislation, etc. Although there is no silver bullet to reduce possible women discrimination in the labor market, perhaps a little of everything may help. For example, gender and minority quotas and a reformed merit-based recruitment may be good for management jobs in the public sector. Another idea might be a social security system that protects female workers' tenure during the period of pregnancy and a period of maternity leave. Equal-pay legislation may also be good in jobs with equal effort, and a better system to pay for job risks and discomforts (disamenities).

One of the main results in this research is that experience (age) is the driving variable behind the wage differential between male and female workers. This is more relevant for management jobs, where experience and responsibility are skills highly demanded. Of course, many women most have a break when motherhood, which affect their careers and participation in the labor market. Social programs to support female workers with the rising costs of childbearing and employment insurance may be some helpful policies to support women to go back to work after maternity leave.

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Annex

Table A2
Two-fold decomposition for managers and professionals in Mexico

Groups/	coef(explained)		coef(unexplained)		coef(unexplained A)		coef(unexplained B)	
Weights	2016Q3	2022Q3	2016Q3	2022Q3	2016Q3	2022Q3	2016Q3	2022Q3
Managers								
$\beta^R = \beta^M$	$ (652.19)	$ (25.16)	$ 1,512.00	$ 2,000.28	$ 1,512.00	$ 2,000.28		
	(443.6)	(385.99)	(561.61)	(531.69)	(561.61)	(531.69)		
$\beta^R = \beta^F$	$ 146.57	$ 830.94	$ 713.24	$ 1,144.18			$ 713.24	$ 1,144.18
	(385.11)	(393.94)	(493.7)	(512.73)			(493.7)	(512.73)
$\beta^R = 0.5$	$ (252.81)	$ 402.89	$ 1,112.62	$ 1,572.23	$ 756.00	$ 1,000.14	$ 356.62	$ 572.09
	(304.58)	(280.01)	(446.98)	(446.22)	(280.8)	(265.85)	(246.85)	(256.37)
$\beta^R = 0.56$	$ (204.11)	$ 454.09	$ 1,063.92	$ 1,521.03	$ 663.82	$ 880.51	$ 400.11	$ 640.52
	(311.31)	(281.23)	(453.15)	(448.72)	(315.04)	(297.64)	(216.75)	(225.7)
Pooled	$ 344.02	$ 1,065.01	$ 515.79	$ 910.11	$ 226.45	$ 400.63	$ 289.34	$ 509.49
	(256.14)	(262.47)	(263.59)	(279.32)	(115.78)	(123.44)	(147.99)	(156.42)
Pooled F	$ 18.36	$ 633.99	$ 841.46	$ 1,341.13	$ 0.00	$ (0.00)	$ 841.46	$ 1,341.13
	(297.38)	(277.02)	(433.06)	(412.86)			(433.06)	(412.86)
Professionals								
$\beta^R = \beta^M$	$ (775.63)	$ (442.38)	$ 890.09	$ 753.05	$ 890.09	$ 753.05		
	(130.93)	(165.73)	(152.42)	(205.18)	(152.42)	(205.18)		
$\beta^R = \beta^F$	$ (423.58)	$ (373.90)	$ 538.04	$ 684.57			$ 538.04	$ 684.57
	(99.82)	(104.87)	(149.46)	(162.2)			(149.46)	(162.2)
$\beta^R = 0.5$	$ (599.61)	$ (408.14)	$ 714.07	$ 718.81	$ 445.05	$ 376.52	$ 269.02	$ 342.29
	(84.98)	(100.13)	(128.27)	(158.11)	(76.21)	(102.59)	(74.73)	(81.1)
$\beta^R = 0.56$	$ (586.87)	$ (406.11)	$ 701.33	$ 716.78	$ 412.84	$ 354.22	$ 288.49	$ 362.56
	(86.69)	(102.7)	(128.53)	(159.68)	(81.73)	(108.67)	(69.32)	(76.29)
Pooled	$ (340.03)	$ (234.18)	$ 454.49	$ 544.85	$ 210.80	$ 256.29	$ 243.69	$ 288.57
	(64.8)	(70.03)	(86.98)	(108.85)	(40.46)	(51.15)	(46.58)	(57.76)
Pooled F	$ (566.76)	$ (438.23)	$ 681.22	$ 748.90	$ 0.00	$ 0.00	$ 681.22	$ 748.90
	(74.42)	(82.28)	(130.48)	(149.49)			(130.48)	(149.49)

Estimates in real Mexican Pesos of 2018. Negative amounts are in parenthesis after the simbol $. Below each amount the standard deviation is presented in parenthesis. All estimates and graphs were obtained using the Package Oaxaca in R by Hlavac, M. (2014).

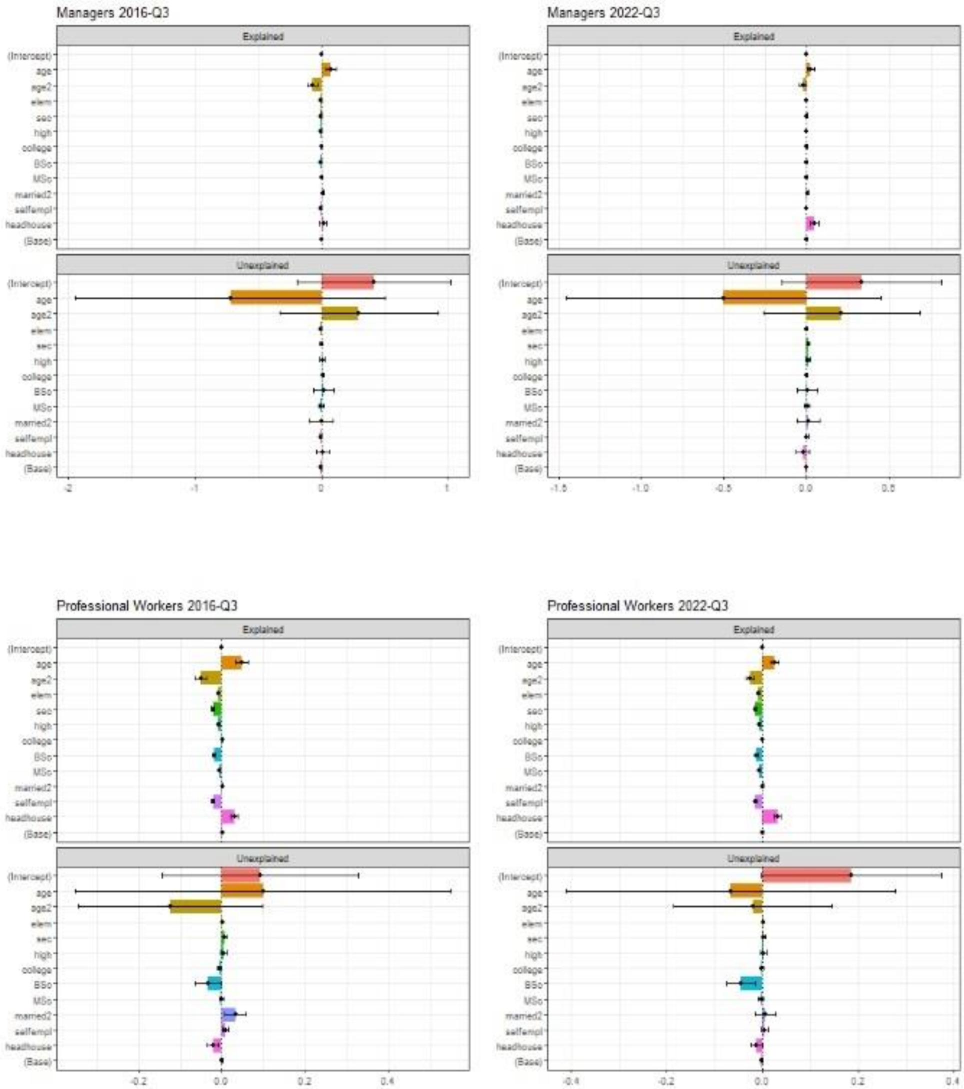

Figure A1. Oaxaca-Blinder two-fold decomposition for Managers and Professionals

http://dx.doi.org/10.22201/fca.24488410e.2025.5393

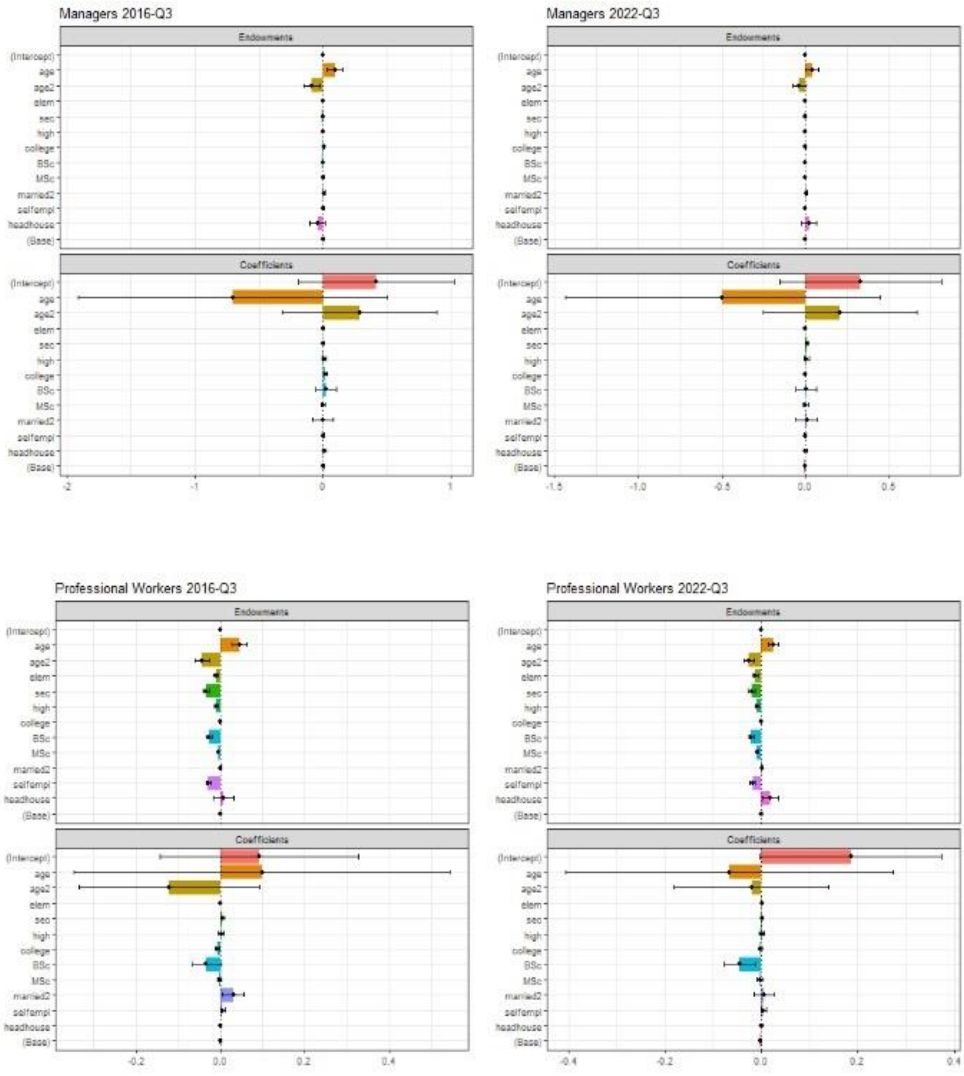

Figure A2. Oaxaca-Blinder three-fold decomposition for Managers and Professionals

http://dx.doi.org/10.22201/fca.24488410e.2025.5393

	Male		Female		Pooled M		Pooled F	
Predictors	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*
(Intercept)	8.4438 ***	0.2132	8.1625 ***	0.2636	8.3153 ***	0.1608	8.3213 ***	0.1607
age	0.0315 ***	0.0091	0.0503 ***	0.0119	0.0400 ***	0.0069	0.0411 ***	0.007
age2	-0.0003 **	0.0001	-0.0005 ***	0.0001	-0.0004 ***	0.0001	-0.0004 ***	0.0001
elem	-0.7339 ***	0.1646	-0.6533 **	0.2029	-0.7389 ***	0.1263	-0.7424 ***	0.1262
sec	-0.3625 **	0.136	-0.4935 **	0.1503	-0.4165 ***	0.1003	-0.4227 ***	0.1003
high	-0.2537	0.1305	-0.4535 **	0.1392	-0.3398 ***	0.0951	-0.3435 ***	0.0951
college	-0.0826	0.1517	-0.4871 **	0.1482	-0.3003 **	0.1053	-0.2985 **	0.1052
BSc	-0.0603	0.1261	-0.2214	0.1324	-0.133	0.0914	-0.1339	0.0914
MSc	0.086	0.1331	-0.0268	0.1405	0.0336	0.0967	0.0331	0.0967
married2	0.1011	0.054	0.1036 **	0.0369	0.1015 ***	0.0297	0.1142 ***	0.0304
selfempl	-0.1789 *	0.076	-0.0567	0.1152	-0.1440 *	0.0629	-0.1472 *	0.0629
headhouse	0.0365	0.0474	-0.0804	0.0626	0.0267	0.0261	-0.0112	0.0328
female							-0.0527	0.0278
Observations	1831		1433		3264		3264	
R^2 / R^2 adjusted	0.086 / 0.080		0.096 / 0.089		0.086 / 0.083		0.087 / 0.084	

* *p<0.05* ** *p<0.01* *** *p<0.001*

2022Q3

	Male		Female		Pooled M		Pooled F	
Predictors	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*
(Intercept)	9.0879 ***	0.2007	9.0897 ***	0.2456	9.0924 ***	0.1515	9.1089 ***	0.1514
age	0.0111	0.0078	0.0241 *	0.0104	0.0148 *	0.006	0.0160 **	0.006
age2	-0.0001	0.0001	-0.0002	0.0001	-0.0001 *	0.0001	-0.0002 *	0.0001
elem	-0.0407	0.1774	-0.5035 *	0.2104	-0.199	0.1352	-0.2049	0.135
sec	-0.2583 *	0.1298	-0.7150 ***	0.1498	-0.4305 ***	0.0979	-0.4315 ***	0.0977
high	-0.1935	0.1233	-0.5780 ***	0.1448	-0.3281 ***	0.0937	-0.3320 ***	0.0936
college	-0.1807	0.1499	-0.5111 **	0.1584	-0.3006 **	0.1077	-0.2941 **	0.1076
BSc	-0.0301	0.1195	-0.3697 **	0.1412	-0.1486	0.091	-0.1509	0.0909
MSc	0.0456	0.126	-0.3069 *	0.1466	-0.082	0.0953	-0.0807	0.0952
married2	0.1042 *	0.0494	0.0884 **	0.0327	0.0777 **	0.0269	0.0982 ***	0.0276
selfempl	-0.2130 **	0.0789	-0.2449 **	0.0864	-0.2182 ***	0.0583	-0.2221 ***	0.0582
headhouse	0.0513	0.045	0.0454	0.0542	0.0957 ***	0.0248	0.0423	0.0299
female							-0.0783 **	0.0245
Observations	1741		1369		3110		3110	
R^2 / R^2 adjusted	0.048 / 0.042		0.080 / 0.073		0.063 / 0.060		0.066 / 0.062	

* *p<0.05* ** *p<0.01* *** *p<0.001*

Figure A3. Regressions for Managers in Mexico

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	Male		**Female**		**Pooled M**		**Pooled F**	
Predictors	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*
(Intercept)	8.0776 ***	0.0822	8.0339 ***	0.0974	8.0348 ***	0.0625	8.0528 ***	0.0624
age	0.0461 ***	0.0031	0.0433 ***	0.0038	0.0460 ***	0.0024	0.0470 ***	0.0024
age2	-0.0005 ***	0	-0.0004 ***	0	-0.0005 ***	0	-0.0005 ***	0
elem	-0.4829 ***	0.065	-0.5582 ***	0.1082	-0.4828 ***	0.0516	-0.4986 ***	0.0516
sec	-0.4423 ***	0.0607	-0.6531 ***	0.0744	-0.4630 ***	0.0464	-0.4783 ***	0.0463
high	-0.3218 ***	0.0602	-0.3915 ***	0.0695	-0.3317 ***	0.0455	-0.3399 ***	0.0454
college	-0.2905 ***	0.0637	-0.2463 ***	0.0698	-0.2582 ***	0.0469	-0.2522 ***	0.0469
BSc	-0.1226 *	0.0589	-0.1233	0.0667	-0.1219 **	0.0442	-0.1179 **	0.0442
MSc	0.0367	0.0636	0.0162	0.07	0.0242	0.0471	0.0306	0.047
married2	0.1033 ***	0.0193	0.0493 ***	0.0145	0.0539 ***	0.0112	0.0732 ***	0.0115
selfempl	-0.1842 ***	0.0159	-0.2653 ***	0.024	-0.2014 ***	0.0131	-0.2113 ***	0.0132
headhouse	0.0191	0.0187	0.0196	0.0312	0.0716 ***	0.0115	0.0191	0.0135
female							-0.0790 ***	0.0106
Observations	10409		9004		19413		19413	
R^2 / R^2 adjusted	0.119 / 0.118		0.117 / 0.116		0.112 / 0.112		0.115 / 0.114	

** p<0.05 ** p<0.01 *** p<0.001*

2022Q3

	Male		**Female**		**Pooled M**		**Pooled F**	
Predictors	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*
(Intercept)	8.7308 ***	0.0646	8.7081 ***	0.073	8.7216 ***	0.0483	8.7418 ***	0.0483
age	0.0269 ***	0.0025	0.0287 ***	0.0029	0.0277 ***	0.0019	0.0285 ***	0.0019
age2	-0.0003 ***	0	-0.0003 ***	0	-0.0003 ***	0	-0.0003 ***	0
elem	-0.4810 ***	0.0519	-0.8443 ***	0.0956	-0.5487 ***	0.042	-0.5675 ***	0.042
sec	-0.3850 ***	0.0455	-0.6206 ***	0.0582	-0.4413 ***	0.0345	-0.4580 ***	0.0345
high	-0.2928 ***	0.0445	-0.4720 ***	0.0492	-0.3548 ***	0.0329	-0.3648 ***	0.0329
college	-0.1909 ***	0.0505	-0.3178 ***	0.0521	-0.2479 ***	0.0363	-0.2453 ***	0.0362
BSc	-0.1361 **	0.0431	-0.2366 ***	0.0458	-0.1835 ***	0.0315	-0.1814 ***	0.0314
MSc	-0.0026	0.0478	-0.1378 **	0.0488	-0.0723 *	0.0341	-0.066	0.034
married2	0.0594 ***	0.0169	0.0473 ***	0.0131	0.0397 ***	0.01	0.0561 ***	0.0102
selfempl	-0.1389 ***	0.0141	-0.1854 ***	0.0198	-0.1470 ***	0.0114	-0.1551 ***	0.0114
headhouse	0.0517 **	0.0167	0.0505 *	0.0258	0.0860 ***	0.0108	0.0419 ***	0.0122
female							-0.0720 ***	0.0092
Observations	11577		10282		21859		21859	
R^2 / R^2 adjusted	0.079 / 0.078		0.076 / 0.075		0.073 / 0.073		0.076 / 0.075	

** p<0.05 ** p<0.01 *** p<0.001*

Figure A4. Regressions for professional workers in Mexico