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Article

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Employment, wages, and the gender gap in Mexico: Evidence of three decades of the urban labor market

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ABSTRACT

This paper analyzes the historical evidence of the gender gap in employment and wages in Mexico. We construct consistent time series from 1988:Q1 to 2019:Q4 using employment surveys, and estimate a model of labor participation in the formal market and wages for each gender and quarter, correcting selection biases. Based on these results, we implement a Blinder–Oaxaca (1973) and Mulligan–Rubinstein (2008) decomposition to estimate the gender gap in wages. Our results suggest the returns to schooling for both genders have decreased in the last two decades, showing a gap of almost 2% in favor of women. The gender wage gap fluctuates around 29.6% once self-selection bias is corrected. The prevalence of differences in expected wages between genders exists due to the "selection bias" and "residual" effects. This work's main limitation is that it focuses only on formal urban employment in 16 metropolitan areas; however, this approach makes it possible to identify long-term trends and structural changes in this market, expanding the evidence of the gender gap in the Mexican economic history.

Resumen: El objetivo de este artículo es analizar la evidencia histórica de la brecha de género en el empleo y los salarios en México. Para ello, construimos series de tiempo consistentes desde 1988:Q1 hasta 2019:Q4 utilizando encuestas de empleo en México, y estimamos en cada trimestre un modelo de participación laboral y salarios para cada segmento de género del mercado formal, corrigiendo el sesgo de selección correspondiente. A partir de estos resultados, implementamos una descomposición Blinder–Oaxaca (1973) y Mulligan–Rubinstein (2008) para estimar la brecha salarial de género. Nuestros resultados sugieren que los rendimientos de la escolaridad para ambos géneros han disminuido en las dos últimas décadas, mostrando una brecha de casi 2% a favor de las mujeres. La diferencia salarial entre ambos sexos fluctúa en torno al 29.6% una vez corregido el sesgo de autoselección. La prevalencia de las diferencias en los salarios esperados entre géneros existe debido a los efectos de "sesgo de selección" y "residual". Una limitación de este trabajo es que sólo se centra en el empleo urbano formal en 16 áreas metropolitanas; sin embargo, este enfoque permite identificar las tendencias de largo plazo y los cambios estructurales en este mercado, expandiendo la evidencia de la brecha de género en la historia económica mexicana.

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1. Introduction

The labor market and its outcomes are fundamentals of any society for achieving economic growth and promoting development. Thus knowing this institution's structure allows identifying the strengths of the complex relationships existing in an economy. Theoretically, economic growth depends on technology, capital, and labor (Arrow et al., 1961), the latter presenting observable and unobservable structural problems. For example, participation or non-participation in the labor market, participation in formal or informal employment, the gender wage gap, and sociodemographic characteristics such as age and sex are observable structural problems. On the other hand, unobservable ones include motivation, persistence, delayed gratification, grit, and other non-cognitive abilities typically not observed. These problems directly affect the development of countries, and emerging economies are the most affected due to the barriers these structures generate (OECD, 2020).

In the case of Mexico, it is difficult to analyze the labor market due to its multidimensionality and structural components. For example, Alcaraz et al. (2008) show that informal employment is a structural problem in the Mexican labor market and that it presents problems for measuring the entire market. Moreover, this labor market segment has significant differences in labor productivity, inducing a more rigid recomposition arising from reallocating workers in the labor market between formal and informal employment.

These structural deficiencies negatively affect economic growth, and central banks can cushion them because the banks play a crucial role in guaranteeing economic and financial stability through monetary policies to maintain stable prices (International Monetary Fund, 2020). Although central banks' primary objective is to keep inflation low, studying market structures is essential for these institutions because these structures can indirectly interfere with their monetary policies through the potential output gap, which is a crucial variable for estimating the interest rate (Guisinger et al., 2018).

For this reason, analyzing the economy's structural components such as labor participation, wages, returns to schooling, and gender wage gaps from an economic and market perspective are of interest in public policy agendas for governments or non-profit organizations and central banks. In addition, understanding the nature of gender differences allows for designing appropriate public policies to correct them and understanding each agent's complex relationships and decisions in the market.

The present study aims to estimate and analyze the historical evolution of average returns to schooling and use these results to identify the decomposition of the gender wage gap for the formal labor market in Mexico over the period 1988:Q1 to 2019:Q4. Our analysis identifies this average gap's observable (defined by the observed coefficients and variables in wage determination) and unobservable (acting through selection bias) effects. For this purpose, we use a micro-based approach based on economic models of labor supply, emphasizing the importance of having historically comparable databases, taking advantage of the various employment surveys conducted in Mexico for more than three decades. We have called on this time series approach based on micro-founded estimates because it combines the micro-econometric analysis of each quarterly database. Moreover, when the database is standardized, the results are used to build a long-term historical analysis.

Our work contributes to the economics and gender economics literature in three areas. First, our work uses quarterly databases constructed in a consistent and micro-founded manner for the labor market, also using standardized definitions for the primary employment and wage variables. This is achieved by using as a basis the Mexican employment surveys conducted by INEGI from 1988:Q1 to 2019:Q4, using a sample of metropolitan areas that are kept constant throughout the entire sample period, making the estimates comparable over time. Second, we make cross-sectional, quarterly estimates. With these estimates, time series are constructed, some of them being original and pioneering in gender economics, such as the returns to schooling between genders, the wage gap between men and women, the gap's observable and unobservable components, and the wage gap's selection bias, among others. Having these series allows understanding the historical picture continuously, not only to identify the existing gender differences but also to understand their structure. Finally, our work addresses the gender issue from an economic context; thus, our objective is not to identify the differences because of "potential discrimination" but to analyze them from a more profound approach. Through this approach, not only do the differences between these groups matter, but also their decisions and interrelationships with the various economic agents in the market play an important role in eradicating their gaps.

This paper is organized into six sections, including this introduction. The second section presents diverse literature and previous research on the structure of the labor market in Mexico and the implicit relationship with monetary policy. The third section presents the characteristics and criteria for homologation in the databases and the main variables used in our study. The fourth section shows the methodology and empirical strategy implemented to estimate and analyze the returns to schooling and the decomposition of the gender wage gap. The fifth section presents the results obtained from the analysis. Finally, the sixth section concludes the study and presents the results' implications.

2. Labor participation, monetary policy, and structural labor market barriers

2.1. Potential female labor force participation

The labor market comprises a set of interactions between economic agents. These simultaneous interactions generate structures that are not always efficient, which is the case of gender differences in the labor market. Different indicators can measure gender differences in the labor market. Some of these indicators include labor participation and observed wages, which are limited metrics for attributing gender differences because there are observable factors (education, marital status, age) and unobservable factors (preferences for leisure, use of time, skills) that correlate with the existence of gender gaps (Cuellar & Moreno, 2022) Nevertheless, analyzing observed variables, such as women's potential labor participation, can show the magnitude of the problem in the deficiency of labor structures, such as returns to schooling and gender wage differentials.

Table 1
Descriptive statistics of women's potential labor force participation rate.

	Shares (%)					
	First decade (1989–1989)		Second decade (1999–2009)		Third decade (2010–2019)	
	Total	Urban	Total	Urban	Total	Urban
Potential Labor Force Participation Rate (PLFPR)	91.47	91.47	90.77	90.74	90.55	89.17
Ratio PLFPR/LFPR	161.83	161.83	141.11	123.86	130.34	107.52
Potential Working Age						
16–25	33.98	33.98	33.42	33.65	33.01	33.88
26–35	24.80	24.80	22.59	21.70	19.77	17.45
36–45	18.86	18.86	18.56	18.37	18.16	17.62
46–55	13.97	13.97	14.58	14.96	15.78	16.50
56–65	8.39	8.39	10.86	11.32	13.28	14.57
Composition of PLFPR						
Student	21.56	21.56	23.60	26.52	27.31	31.23
Housewife	78.44	78.44	76.40	73.48	72.69	68.77
Family Status of PLFPR						
No Children	14.23	14.23	22.49	22.85	36.36	38.19
Children	85.77	85.77	77.51	77.15	63.64	61.81
Female Not Potential Labor Force Participation						
Disability	0.53	0.53	0.63	0.63	0.80	0.81
Retired	1.64	1.64	1.98	3.02	3.37	5.53

Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019).

Table 1 shows the descriptive statistics on the proportions of economically inactive women in Mexico who could potentially be part of the labor market because they are of age, do not have a disability or are not retired. The Potential Labor Force Participation Rate (PLFPR) in the last three decades represented about 90% of women who were not economically active; comparing this with female employment, the PLFPR (women with possibilities of working) represents 1.3 times the female labor force of the last decade; on the other hand, 60% of these women were within the productive age range to generate maximum income (26 to 55 years).

The composition of the PLFPR in the last three decades has remained stable; 25% are female students while 75% are female homemakers. The main component of the PLFPR (housewife) is considered unpaid work, which for Mexico, in intrinsic value, represents 5.6 trillion pesos in 2019, equivalent to 22.8% of the Gross Domestic Product (Instituto Nacional de Geografía, 2020). This situation generates female employment labor structure deficiencies; therefore, understanding why these women are not working can be a starting point. One of the reasons women decide not to work could be that about 75% of the PLFPR are women with at least one child, which may represent a barrier to entering the market.

Finally, Table 1 shows that not even 3% of women who are inactive in the labor market are disabled or retired, meaning that there is a potential problem of non-participation in the labor market. This is reflected in the low percentage of women's labor participation in Mexico compared to other emerging economies in Latin America, such as Argentina, Brazil, Chile, Colombia, and Peru (Fig. 1).

According to data from the International Labor Organization (2021), female labor participation in Mexico is the lowest among emerging Latin American economies. The most recent data for Mexico, from 2019, shows that, on average, women represent 45.8% (Fig. 1). In relative terms to the other countries, this represents a gap of 12 years with Chile, while this gap already existed for 20 years with the other countries. For example, in the 1990s, Colombia's female labor force represented 50.71% of the labor market, while only 33.7% for Mexico.

According to economic theory, this indicator responds to real wage and income stimuli. Therefore, the link between the labor structure and economic growth and the output gap is of institutional interest (Tylor, 1993). This is especially true for central banks because understanding the market's structure would allow them to make better decisions if the banks' objectives included maintaining long-term economic stability.

2.2. Monetary policies and their relationship to labor market structures

The main objective of central banks is to conduct a monetary policy to achieve price stability (low and stable inflation). In some developed economies, stabilizing policies are also sought to reduce the output gap (International Monetary Fund, 2020).

One of the primary keys to achieving a stabilizing policy is to measure the output gap. This indicator depends implicitly on the potential labor supply, which in turn depends on the structural barriers existing in the market. Therefore, if central banks study the labor market's structural barriers and the market's components (e.g., gender differences in potential labor participation, returns to schooling, and gender wage gaps), they could use these micro-foundations to set more effective monetary policies.

Until now, there is no single theoretical method for measuring the output gap, which complicates central banks' policy decisions. The lack of a standardized methodology is particularly true for low-income ones considering deviating from the main objective (keeping the inflation rate low and stable) may discredit their monetary policies (International Monetary Fund, 2015).

Guisinger et al. (2018) study six measures for calculating the output gap in the United States and show how different measurement methods have implications in real terms on monetary policy decisions. Currently, the Congressional Budget Office (CBO) uses a model

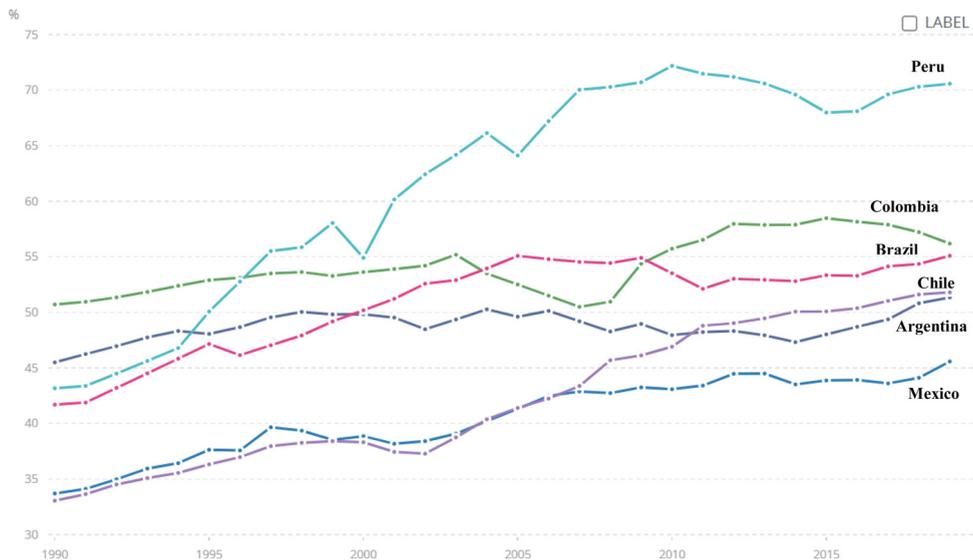


Fig. 1. Labor force participation rate, female (% of female population ages 15+) (modeled ILO estimate) – Mexico, Colombia, Argentina, Brazil, Peru, and Chile

Source: World Bank (2021).

for measuring the potential output gap by attributing real economic growth to three factors of production: capital, labor, and economic progress.. They divide Gross Domestic Product into five sectors: non-farm business, government, farm, households and non-profits, and housing. Once the factors of production and sectors have been identified, the estimates are based on Cobb–Douglas models of production, estimating potential values of labor, capital accumulation, and the total factor productivity (TFP). Nevertheless, as mentioned above, the differences in metrics for measuring potential gaps differ, such as in the case of Mexico, which does not have a dual mandate in its policies. Because of this, the estimation methodology used is more deterministic, that is, using the Hodrick–Prescott (HP) filter with tails correction to estimate the output gap, thus generating an estimation of bands that use the methodology of unobserved components (Harvey, 1990).

The output gap's accurate estimation implies that central banks can also have policies that are more efficient because, for example, the Tylor rule (1993), which is characterized as an optimal monetary policy rule, establishes that the interest rate is a function of the deviation from inflation and target inflation, and a function of the potential output gap.

Thus, once the link of the implicit relationship existing between structural barriers to labor market entry and monetary policy decisions has been understood, the following section presents the micro-founded structural analysis of these market barriers.

2.3. Structural barriers between genders in the Mexican labor market: stylized facts

Analyzing labor market deficiencies has its complexities, considering there are various metrics to address them; in this study, we estimate these deficiencies from a gender perspective, analyzing these structural barriers through differences in expected wages.

Many researchers have contributed various papers on the gender wage gap topic in different countries, including Mexico. Most of the empirical studies estimate gender wage gaps to explain these differences. There are several methodologies for estimating wage gaps, which are described below.

For Mexico, there is abundant literature in this area. For example, Brown et al. (1999), Martínez and Acevedo (2004), Popli (2013), Arceo and Campos (2014) and finally, Castro et al. (2015) have conducted studies on the wage gap and labor participation in Mexico. The importance of discussing these authors' works lies in the methodology used to address these issues because most of them differ in the methodology employed.

Brown et al. (1999) use Wellington's (1993) decomposition to explain the differences between gender wage gaps and report that investment in human capital between 1987 and 1993 explains a more significant proportion of the increase in the wage gap. In addition, during this same period, Mexican women were underrepresented in the professional category, and some occupational categories were overrepresented. Finally, they conclude that the male–female decomposition shows that the wage gap in Mexico increased from 1987 to 1993, an increase that they attribute to the differences in rewards between men and women. However, occupation later controls this.

Martínez and Acevedo (2004) use equations based on Mincer (1975), and with this, they compare the wage gaps between men and women. The study suggests that the wage structure affects 85% of discrimination. In comparison, the higher marginal productivity of women compared to men, which is not reflected in the salary received, explains the other 15%.

Popli (2013), Moreno (2007), Arceo and Campos (2014), Castro et al. (2015) and Martínez and Acevedo (2004) emphasize the importance of correcting for selection bias. All four use the Blinder (1973) and Oaxaca (1973) methodology to estimate gender wage gaps; although, for his part, Popli (2013) uses two more methodologies as a comparison.

Popli (2013) analyzes the 1996 and 2006 gender wage gap in the formal and informal sectors, considering the probability of employment in the wage sector. In his research, he compares three methodologies: Oaxaca–Blinder decomposition, non-parametric methodology (multinomial logit), and Jenkins’s decomposition. The author finds that all three methodologies indicate that, on average, wage discrimination has decreased over time. In addition, the Jenkins measure shows that discrimination has decreased across the distribution; comparing each percentile in 1996 with those in 2006, Popli (2013) finds that women’s percentiles are relatively higher compared to men’s in both sectors. In contrast, the non-parametric methodology yields evidence of the "glass ceiling metaphor," with the highest part of the distribution being the most affected.

Arceo and Campos (2014) analyze the wage gap’s evolution in Mexico from 1990 to 2010. For their analysis, they use the 1990, 2000, and 2010 Population and Housing Censuses and the National Employment Survey (ENE) for the period from 1989 to 2012 and the National Household Income and Expenditure Survey (ENIGH) from 1989 to 2012. The authors use a semi-parametric method to explain gender wage differences in the period analyzed, obtaining as main results that, on average, wage gaps have decreased, and they find a stable "sticky floor" pattern and a decreasing "glass ceiling" pattern with the distribution in those periods. In addition, they find a positive selection, after correction, which focuses on women with low education and in low quartiles.

Finally, Castro et al. (2015) study Mexico’s northern border, finding significant wage differences between men and women. Furthermore, after correcting for selection bias using Heckman’s (1977) methodology, their estimators are more robust, having a difference of at least 2% compared to their estimators without correcting for selection.

Based on the previous literature, several methodologies exist to estimate gender wage gaps. Some emphasize the importance of correcting for selection bias, while others only seek to find differences at two different time points. For this reason, this research’s main contribution is to estimate and analyze gender wage gaps from a historical and micro-founded perspective, which allows us to construct quarterly time series of the observable and unobservable gender components for the formal labor market. From this, we can capture the structural behavior based on the estimates’ trends. Furthermore, an extension to the model Blinder (1973) and Oaxaca (1973) proposed will be implemented to capture the unobserved heterogeneity in the formal labor market. As a first step, we will estimate the average returns to schooling across groups and then estimate the gender wage gap for Mexico.

3. Data

3.1. Sources of information

For the analysis, we standardized three existing employment surveys the National Statistics and Geography Institute (INEGI) conducted: the Urban Employment Survey (ENEU) for the years 1988 to 2000, the National Employment Survey (ENE) for the years 2001 to 2004, and the National Occupation and Employment Survey (ENOE) for the years 2005 to 2019. These databases were standardized to perform cross-sectional micro-estimations and build aggregate data series based on variables and estimations based on the labor market’s micro-foundations. INEGI collects the ENEU, the ENE, and the ENOE to capture data on employment and sociodemographic characteristics in Mexico. The first two surveys precede the current ENOE. These surveys are a rotating panel with substitution. An individual household is followed for up to five consecutive quarters, and 20% of the sample is replaced each quarter. For the present research, we take advantage of the cross-sectional data to estimate and construct non-existent series of quarterly aggregate data (i.e., time series of employment, schooling, real wages, returns to schooling, and wage gaps) because we are interested in obtaining the behavior in the aggregate of these series.

Based on the above, and for this analysis, the construction of the micro-based time series is limited to individuals between 16 and 65 years of age who are working and receiving a monetary labor income greater than zero, thus excluding individuals who work without receiving any payment or remuneration and individuals who work in the informal sector.

Regarding formal employment, we adhere to the definition of our previous research (Moreno & Cuellar, 2021), where for the case of salaried workers, we refer to whether the person has social security (IMSS or ISSSTE).¹ In the case of employers, subcontractors, and self-employed workers, we decided to opt for the number of workers employed (at least more than 15 people) and whether the company name is duly registered. On the other hand, we excluded the agricultural sector from the sample.

Given that one of our main research contributions is the homologation of existing employment surveys for Mexico, it was necessary to impose certain restrictions to achieve this. One of them was that our sample only follows 16 metropolitan areas over time (Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo). We did this to reduce the inclusion bias because these metropolitan areas are maintained in all surveys over time; this may seem to be a limitation of our work. However, note that these 16 metropolitan areas represent almost 70% of urban employment in the entire country throughout the period analyzed (see Appendix: Fig. A1). Finally, we exclude all rural areas for homologation purposes because the ENEU only includes urban areas in Mexico.

3.2. The labor market in México: descriptive statistics

Section 2.1 described the low labor participation of female employment in Mexico, but this behavior persists in the aggregate market. Table 2 shows a comparison between the last three decades. For example, the economically active population has remained constant over the three decades at around 46.12%, and for urban areas, it only represents one percentage point more.

¹ Instituto Mexicano del Seguro Social (IMSS) or Instituto de Seguridad y Servicios Sociales de los Trabajadores del Estado (ISSSTE).

Table 2
Labor market statistics.

	Shares (%)					
	First decade (1989–1998)		Second decade (1999–2009)		Third decade (2010–2019)	
	Total	Urban	Total	Urban	Total	Urban
Economically Active Population	51.46	51.46	42.38	44.22	44.52	46.44
Salaried employment	92.99	92.99	91.30	90.21	89.77	87.96
Formal salaried employment	45.95	45.95	37.51	45.80	35.77	44.70
Survey Population (N)	22,607,323	22,607,323	96,195,095	46,031,540	122,677,335	51,854,150

Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019).

Table 3
Composition of the female labor market in Mexico.

	First decade (1989–1998)		Second decade (1999–2009)		Third decade (2010–2019)	
	Total	Urban	Total	Urban	Total	Urban
Labor Force Participation Rate (LFPR)	17.96	17.96	15.45	17.23	16.93	19.46
Salaried workers	90.20	90.20	88.74	87.47	89.74	86.58
Salaried workers (Cohorts)						
16–25	40.13	40.13	24.03	23.15	19.90	18.98
26–35	29.99	29.99	28.21	29.03	25.55	25.19
36–45	18.40	18.40	25.82	26.19	26.46	26.47
46–55	8.44	8.44	15.52	15.78	19.18	20.22
56–65	3.05	3.05	6.41	5.85	8.91	9.13
Marital status of salaried workers						
Single	46.70	46.70	36.55	38.09	31.97	34.31
Married	34.54	34.54	38.72	38.13	36.97	35.74
Free Union	4.30	4.30	8.60	8.00	14.58	13.71
Divorced	2.82	2.82	2.93	3.53	2.95	3.51
Separate	6.00	6.00	7.29	7.33	7.94	7.81
Widower	5.64	5.64	5.90	4.91	5.60	4.92
Family status of salaried workers						
Household Head (HH)	11.24	11.24	14.42	15.78	19.21	22.26
HH with no children	7.26	7.26	7.91	8.63	10.54	12.69
HH with children	92.74	92.74	92.09	91.37	89.46	87.31
HK composition of salaried workers						
No Education	4.84	4.84	6.38	3.54	4.27	2.31
Primary	29.77	29.77	29.70	24.23	24.45	17.39
Secondary	17.59	17.59	23.07	23.48	28.55	25.19
High school	7.31	7.31	11.85	13.10	18.18	19.44
Technical	25.79	25.79	12.82	15.55	6.54	10.19
Bachelor	13.74	13.74	15.17	18.68	16.64	20.96
Postgraduate	0.96	0.96	1.01	1.43	1.38	2.06
Women survey population (N)	11,844,758		49,343,495		62,194,478	

Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019).

For almost 50% of the working population, on average, salaried employment remains at 90% for the entire country and urban areas. In comparison, 40% of this employment is formal employment throughout the country and 45% in urban areas.

Specifically for Mexican women, the picture becomes murky regarding labor participation. Over the last three decades, the representation has been low and constant, being in the last decade for urban areas, only 19.46%. However, 90% of women have salaried employment throughout Mexico and only in urban areas.

Four characteristics of the female labor force stand out: age, marital status, family status, and human capital (Table 3). Over the three decades, more than 50% of the female labor force comprises women between 26 and 55 years of age, the productive labor cycle. On the other hand, regarding the labor force's marital status, about 30% of the women are married, highlighting the status of the free union, which has increased in its composition by about 70% in the last decade. Regarding family status, on average, 15% of women are heads of households, and more than 90% have at least one child.

Finally, human capital is one of the labor market's main characteristic components; here, women have shown substantial increases in it. Of the women, 16.64% and 20.96% have a bachelor's degree nationwide and in urban areas in the last decade. Additionally, in the last decade, in urban female employment, only 2.31% have no education whatsoever. Thus human capital is a component of heterogeneity in the labor market for women, making it interesting to study it.

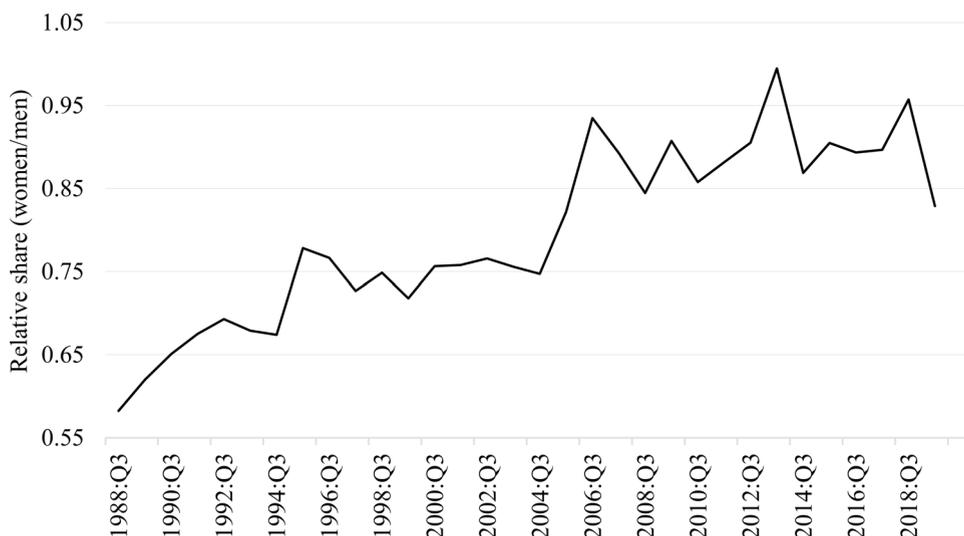


Fig. 2. Women's to men's labor force participation rate, 1988:Q3–2019:Q3

Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: The median of the third quarter of each year of individuals working in the formal sector and receiving non-zero labor income in the urban area is reported. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreón, San Luis Potosí, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juárez, Tijuana, Matamoros, and Nuevo Laredo. Given that our variables of interest are wages, education, and labor participation, we present below a descriptive temporal analysis that shows the averages and medians for the third quarter of each year for each of the variables. This analysis allows us to capture the long-term trend behavior and identify the evolution of gender differences in wages, education, and employment.

3.3. Formal employment, schooling, and real wages: a historical analysis of the structural barriers for women to entering the labor market

Fig. 2 shows the evolution of the women's labor force participation rate in the formal market in Mexico relative to men's. In 1988:Q3, for every man working, there were 0.58 women in the labor market, implying an employment gap of about 42% in the relative participation. However, according to the most recent observation in our study (2019:Q3), the relative participation gap has decreased, with 0.83 women working for every man in the labor market. In this case, our estimates suggest that the employment gap was reduced by only 25% over more than 30 years of history.

One of the peaks in Fig. 2 is the relative ratio of 1995:Q3, representing 0.78 women in the labor market for every man in the market; in terms of percentage changes, this point represents the highest of the entire period analyzed at 15% compared to the previous period. This result can be derived from the "added worker effect," which several authors in labor economics have studied (Cuellar et al., 2022; Gomez & Mosino, 2019; Sokufias & Parker, 2006; Humphries, 1988). These authors propose the female labor market as an escape valve for male employment when a country's economy is in recession. The hypothesis above would explain this phenomenon of the increase observed in the relative rate variable, which is attributed to the crisis that Mexico suffered between 1994 and 1995. Finally, Fig. 2 shows a constant trend on average in the relative rate of labor participation, despite this unfavorable result.

Education is recognized as a pillar in constructing an individual's human capital and so fundamental factor in determining salaries in the market (Becker, 1965; Ben-Porath, 1967; Mincer, 1975). The average woman in the formal labor market in Mexico has completed high school, while the average man has not completed high school. Fig. 3 shows that by 2008 women already reported the same average years of schooling compared to the average men reported in the last observation of the sample (2019:Q3).

On average years of schooling, these data series show observable differences between men and women, which fluctuate between -0.04 to 1.11 years of schooling, with women having a higher average than men have in the formal labor market in urban areas (comparable metropolitan areas in our sample) in Mexico.

Finally, Fig. 4 shows the evolution of median real wages in Mexico. In general, for both genders, real hourly wages have remained stagnant over the last three decades, reporting a median of 40 Mexican pesos per hour on average throughout the period analyzed. In addition, there are differences between genders that fluctuate from 0 to 4 pesos per hour, with men showing higher stability compared to women.

Concerning the above analysis, three aspects are worth noting: (1) The female labor force has not shown an improvement in the last three decades despite having more and better job opportunities. (2) Women have a higher level of education and constitute a more prominent force regarding total size in the labor market. (3) Mexico's real wages have been stagnant for the last 30 years. This last point is serious because, despite having a more stable labor market and higher levels of human capital, the lag and differences between groups prevail. For this reason, our work delves into gender differences in the labor market, identifying the effects attributable to observable factors (wage differentials, returns to schooling) and latent unobservable factors (selection bias and effects attributable to discrimination). The following section shows the econometric strategy for the estimations and then presents the results.

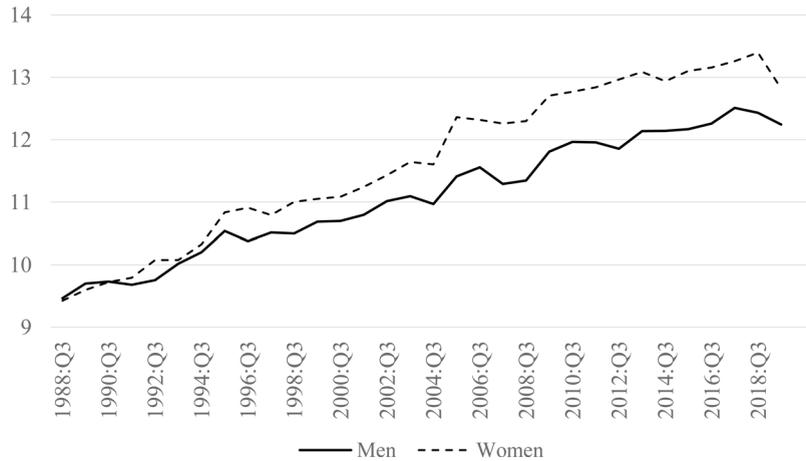


Fig. 3. Average years of schooling by gender, 1988:Q3–2019:Q3

Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: The median of the third quarter of each year of individuals working in the formal sector and receiving non-zero labor income in the urban area is reported. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo.

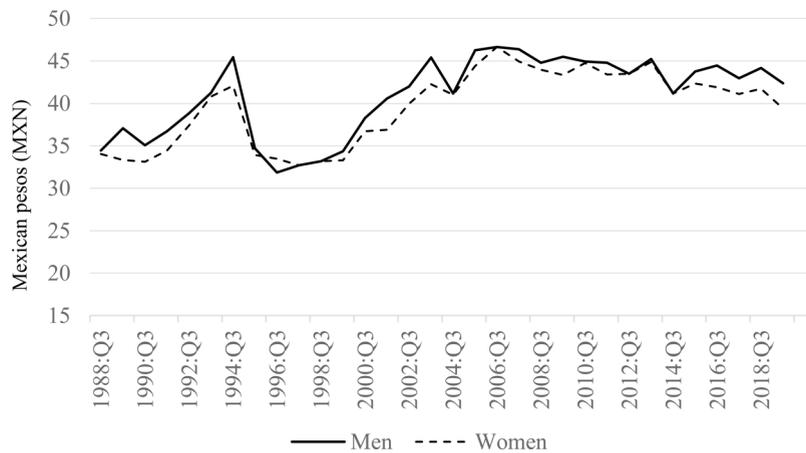


Fig. 4. Median real hourly wages by gender, 1988:Q3-2019:Q3

Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU(1988–2000), ENE(2001–2004), ENOE(2005–2019). Notes: The median of the third quarter of each year of individuals working in the formal sector and receiving non-zero labor income in the urban area is reported. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo.

4. Methodology and empirical strategy

4.1. Wages and returns on education

We used the "Mincerian equation" approach to estimate the returns to average schooling and the gender wage gap based on the original empirical variables Mincer (1975) proposed. Nevertheless, the estimation is performed in two stages: the first stage corresponds to the correction of the self-selection bias as omitted variables (Heckman, 1977), in which a probit model is used to construct the "inverse of Mills' ratio" variable; and the second stage corresponds to estimating the returns to average schooling and estimating the expected wages through integrating the previous estimation as an omitted variable.

Although the approach remains simple regarding the included variable, we gain insight by expanding this comparison for 30 years of different samples in the same metropolitan areas. We use this estimation to construct the formal wage gap between men and women subsequently.

The empirical model proposed is a two-stage model as follows:

Stage 1

$$s_{it}^{j*} = \beta_0 X_{it}^j + \beta_{1t}^{women} chil_{it}^{women} + \beta_{2t}^j Dhh_{it}^j + Dstate_{it}^j + u_{it}^j \tag{1}$$

Where:

$$s_{it}^j = 1 \text{ if } s^* > 0 \text{ (the individual works)}$$

$$s_{it}^j = 0 \text{ if } s^* < 0 \text{ (the individual does not work)}$$

Stage 2

$$\ln(w_{it}^j) = \alpha_{it}^j + \beta_{1t}^j sch_{it}^j + \sum_{n=1}^4 \beta_{(n+1)t}^j (age)_{it}^{jn} + Dstate_{it}^j + \delta_1^j \lambda_{it}^j + \varepsilon_{it}^j \tag{2}$$

$\forall j \in (men, women); t \in (1988 : Q1, 2019 : Q4)$ Where each coefficient is estimated at each cross-section; in other words, we estimate a time series in the coefficients of the Mincerian equation from the estimation for each cross-section in the urban areas considered from 1988:Q1 to 2019:Q4. The first stage estimates a model that captures the probability of an individual working, given the market structure. In Eq. (1), we control for observed variables, X_{it}^j (dummy variables of the individual’s marital status, their average years of schooling, and potential experience), but we also add two instrumental variables for women, $chil_{it}^{women}$ and Dhh_{it}^j (number of children and dummy variable if she is head of household) and for men only if he is head of household, Dhh_{it}^j . These instrumental variables directly relate to the probability that the individual is working but weakly correlates with wages, which allows us to capture the self-selection bias in the sample.

Eq. (1) is implicitly related to the potential output gap estimates because it endogenously estimates the labor market’s composition and structure regarding observed variables and an error term that captures that which cannot be observed. In addition, the inverse Mills ratio is calculated once the model is estimated, which captures the self-selection bias in the sample.

In the second stage, Eq. (2), $\ln w_{it}^j$ is the dependent variable of the model and represents the natural logarithm of the hourly wage for individual i . The set of explanatory variables is the individual’s years of schooling (sch_{it}^j), the individual’s age (age_{it}^j), this being a way of approximating potential experience.² As control variables, we add fixed effects per state, which dichotomous variables³ ($Dstate_{it}^j$) represent. Regarding the unobserved, (λ_{it}^j) is the inverse Mills’ ratio for individual i , which captures and corrects for self-selection bias in the sample. Moreover, the sample and the error term of the individual i is (ε_{it}^j). Finally, it is essential to note that the superscript (j) and the subscript (j) are only indicative; that is, j , they indicate the gender and t the period in which the equation is estimated.

Eq. (2) recovers the econometrically consistent estimators of interest in this study. In this case, the β ’s are the expected returns corresponding to the quarter of estimation of the average individual the model reports, both for education and for potential experience. Once the expected returns and wages are obtained, the extension of the wage gap decomposition (Mulligan & Rubinstein, 2008; Beblo et al., 2003; Dolton & Makepeace, 1986) is performed, and the expected effects of the decomposition are calculated.

4.2. Gender wage gap decomposition and extent of selection bias

To estimate gender wage gaps, we propose an extension to Blinder’s (1973) and Oaxaca’s (1973) methodology, which studies the differences in expected wages between groups. These authors divide the wage differential into two effects: the observed effect, which depends on productivity differences commonly measured through education, potential experience, and sociodemographic characteristics. The other effect is the unobserved effect, which they attribute to discrimination between groups. In addition to capturing "potential discrimination," this unobserved effect could also reflect omitted variables or idiosyncratic errors because it is included as a residual in the model.

The decomposition of the wage gaps uses the "Mincerian equation" as a basis, and with it, we obtain both groups’ expected wages. For this study, we propose an extension to the Blinder (1973) and Oaxaca (1973) model, which allows us to incorporate into the decomposition an additional effect, called the "selection bias effect" (Mulligan & Rubinstein, 2008; Beblo et al., 2003; Dolton & Makepeace, 1986). This effect is incorporated due to unobservable factors, but unlike "potential discrimination," selection bias can potentially capture unobservable effects associated with the endogenous labor participation decision, such as household structure and reservation wages. Given this effect’s relevance, we devote an exclusive section to the results, in which we will elaborate on this issue.

Therefore, the extension of the traditional Blinder (1973) and Oaxaca (1973) model, which Mulligan and Rubinstein (2008) recently implemented, starts from the following assumptions based on Heckman’s (1977) labor supply model:

$$\eta_i^j \sim N(0, \sigma_{\eta}^{2j}) \tag{3}$$

$$\begin{pmatrix} u_i^j \\ v_i^j \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u_i^j u_i^j} & \sigma_{v_i^j u_i^j} \\ \sigma_{v_i^j u_i^j} & \sigma_{v_i^j v_i^j} \end{pmatrix} \right] \tag{4}$$

² Murphy and Welch (1990) proposed this potential experience approach and Card (2001) used it.

³ The dummy or dichotomous variables take values of 1 and 0, depending on the case study.

$$S_i^j = I(v_i^j \geq 0) \forall i = \{1, \dots, N\}, j = \{M, W\} \tag{5}$$

Assumption (3) is the idiosyncratic error term, or unobservable factors for each group, with zero mean and sigma-squared variance. Assumption (4) is a reference for identifying the error terms of the selection equation and the result equation, which are orthogonal to each other and between groups. Finally, assumption (5) is crucial in our study because this is where the effect derived by the selection bias is derived. This indicative variable, known as the "decision rule" concerning the labor market, captures the labor participation of each individual in each group (men and women). In particular, each agent decides to enter the formal labor market if their compensation is at least their reservation wage.

The above elements allow us to identify the structure of the conditional participation model as follows:

$$\begin{aligned} E[\Delta w] &= E[w^M | X_i^M, S^M = 1] - E[w^W | X_i^W, S^W = 1] \\ &= \underbrace{E[X^M - X^W | S^M = 1, S^W = 1] \hat{\beta}^M}_{\text{Endowment effect}} + \underbrace{E[X^W | S^W = 1] (\hat{\beta}^M - \hat{\beta}^W)}_{\text{Remuneration effect}} + \underbrace{E[X^M - X^W | S^M = 1, S^W = 1] (\hat{\beta}^M - \hat{\beta}^W)}_{\text{Interaction effect}} \\ &\quad + \underbrace{E[\lambda^M - \lambda^W] \hat{\delta}^M + E[\lambda^W] (\hat{\delta}^M - \hat{\delta}^W)}_{\text{Self-selection bias effect}} + \underbrace{E[\lambda^M - \lambda^W] (\hat{\delta}^M - \hat{\delta}^W) + (\hat{\alpha}^M - \hat{\alpha}^W)}_{\text{Residual effect}} \end{aligned} \tag{6}$$

Eq. (6) shows the decomposition of the formal gender wage gap, using the difference between the expected wage of men and women, into five effects: endowment, remuneration, interaction, selection bias, and residual ("potential discrimination").

The first effect captures the differences in average observed characteristics between the two groups (men and women). The second shows the differences in the estimated returns given the observed characteristics and their decision rule. Finally, the third effect shows the interaction between the endowment effect and the pay effect.

The selection bias effect captures the difference in the magnitude of selection bias given their participation decision. Finally, the decomposition in Eq. (6) presents the effect of the difference in the constant (α 's), which various authors attribute to "discrimination" between groups (Blinder, 1973; Oaxaca, 1973; Arceo & Campos, 2014). For this study, particular emphasis will be placed on the differences in the observable and unobservable effects, without imposing the effect of the constant as "potential discrimination," but taking it only as an effect that captures the unobserved.

5. Estimation and results

The returns to schooling are estimated using a two-stage "Mincerian" model (Mincer, 1975), which represents individuals' productivity through market wages. The first stage is carried out to correct for self-selection bias in the sample (Heckman, 1977), and in the second stage, we perform the calculation estimation of returns to schooling. Once we analyze the returns, we estimate the gender wage differentials decomposition (Blinder, 1973; Oaxaca, 1973) with an extension to the self-selection bias correction model (Mulligan & Rubinstein, 2008).

First, we will begin by analyzing the returns to schooling between men and women, focusing on the differences in valuation (opportunity cost) that the market determines for these groups. Then, in a second section, we will analyze the decomposition of wage differences between genders, identifying observable and unobservable effects. Finally, we will analyze in detail the unobservable effects, the effect of selection bias, and in a specific case, what we call "potential discrimination."

5.1. The historical evolution of returns to schooling in Mexico

This section calculates the returns to schooling for both genders (Fig. 5). We used a two-stage model (Heckman, 1977), which corrects selection bias in the sample in the first stage, and in the second stage, the returns to schooling are calculated, which captures β_1 (Eq. (2)). We find evidence of positive selection bias for women and negative selection bias for men in both groups as significant. Suppose selection bias is not considered in the calculation of returns to schooling. In that case, the econometric implications are the overestimation of coefficients for women and underestimation of coefficients for men regarding the uncorrected estimate in economic terms.

The time series of returns show fluctuations over time, ranging from 5.7 to 11.3% for women and 6.08–10.2% for men.⁴ The gap between men and women is maintained until the 2000s. From 2001 onwards, this difference is reversed; the returns to schooling show increases for women and decreases for men, with a gap in favor of the first group. This phenomenon could be associated with the heterogeneity of opportunity costs the labor market determines for both groups because, between 2001 and 2005, the international economic environment underwent substantial changes (China's entry into the WTO), which in the case of Mexico, recomposed formal and informal employment, that is, decreases were observed in this same period (Alcaraz & García, 2006; Alcaraz et al., 2008). Given that these differences persist throughout the period analyzed, this would imply that the heterogeneity between more and less educated women than men on equal terms drives the differences in average wages.

Fig. 6 compares the average years of schooling with the returns to schooling. Again, we observe an increasing trend of average years of schooling for both groups, as analyzed in Section 3.3. In contrast, the returns to schooling have increased from 1988:Q1–2000:Q4, while the opposite is observed for 2001:Q4.

⁴ See Appendix B, which presents the returns to schooling micro-estimations time series.

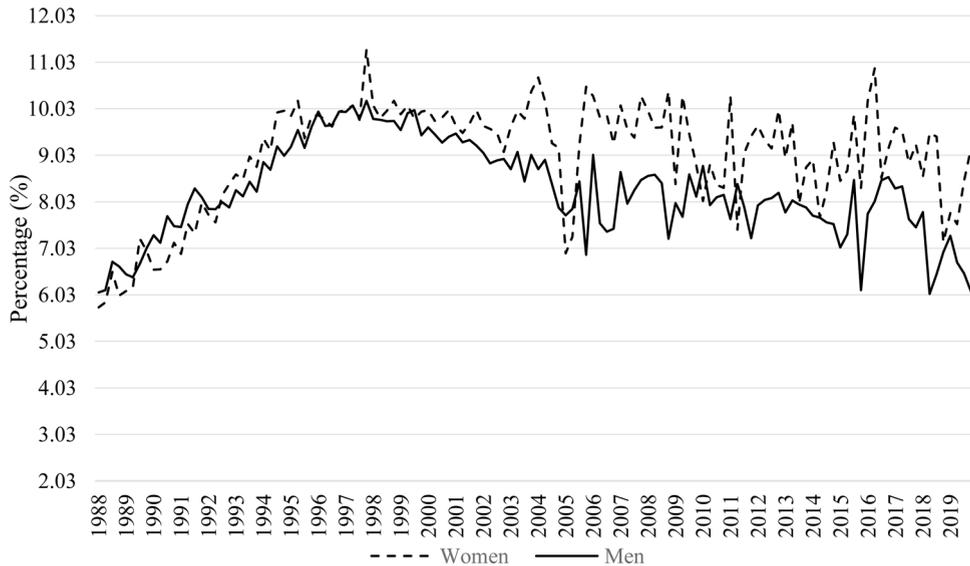


Fig. 5. Returns to schooling by gender, 1988:Q1–2019:Q4

Source: Own estimates with homogenized databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: For returns, each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. Informal employment, persons working without pay, and rural areas are excluded. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo. *Each of the coefficients presented is a percentage and is significant at the 1% level (returns to schooling).

The trend of schooling returns decreasing, while the trend of average schooling increases for both groups (Fig. 6) is a finding that coincides with the result Patrinos (2016) found, which estimated and observed that average schooling returns are decreasing for Latin American countries, including Mexico. Specifically for Mexico, Moreno (2007) and Caamal (2017) also coincide with the finding of decreasing returns to schooling by quantiles, which supports our results because, in his analysis, he uses the ENEU and ENOE for a period similar to this study (1988–2013).

5.2. The historical evolution of gender wage differentials in Mexico

Authors conducting wage gap studies in Mexico obtain point estimates and static differences; they estimate the wage gap for a time point and compare it to another time point (Arceo & Campos, 2014; Brown et al., 1999). The estimates below capture the trend of the formal labor market gender wage gaps calculated from 1988:Q1 to 2019:Q4 (Fig. 6) regarding the methodology and homologation of the variables based on the labor market micro-foundations for Mexico.⁵

Fig. 7 shows a constant pattern of the gap of around 29.6%. After the 1995 crisis, a decreasing gap pattern emerged, reaching a minimum point of 16.8% in 2015:Q1. These gender differences increase again from the following observation, showing a gender wage gap of 36.6% in the formal labor market at the end of this year.

In our estimates, we find evidence of positive selection bias in the wage gap estimates; Fig. 8 conveys this fact, which, without correcting for this unobserved heterogeneity, the wage gap would be substantially underestimated throughout the period studied. In other words, the gender wage gap uncorrected shows differences of around 6.7% on average over 30 years.

These results justify the importance of correcting for self-selection bias in the sample, which has econometric implications and it evidences a substantial increase in the estimation of the gender wage gap in the formal labor sector.

5.3. Decomposition of the gender wage gap in the formal labor market

Based on the model used to calculate the returns to schooling, the gender wage gap in the formal labor market is estimated. We present the results in two sections, the observable effects, and the unobservable effects. Within the observable effects are the endowment, remuneration, and interaction effects; on the other hand, selection bias and residual effects are presented for the potentially unobservable effects.

5.3.1. Effects by observable variables

Fig. 9 shows the decomposition of the gender wage gap in terms of its observable factors. Before continuing, we should point out that these effects are not purely net; that is, their calculation includes the selection bias effect and the residual effect, as we can see

⁵ See Appendix C, which presents the gender wage gap decomposition micro-estimations time series.

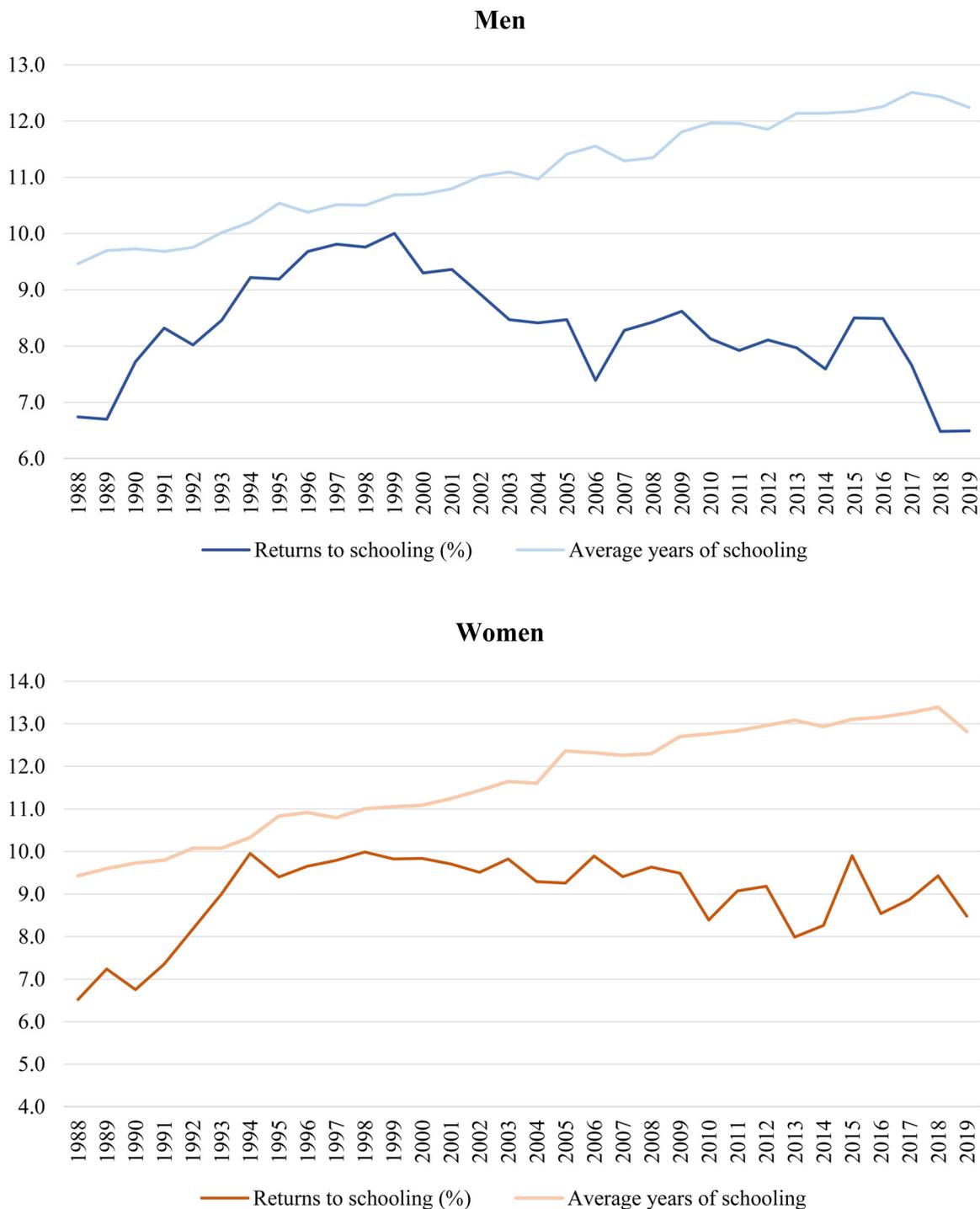


Fig. 6. Returns to schooling and average years of schooling, 1988:Q1–2019:Q4

Source: Own estimates with homogenized databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: For returns, each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. Informal employment, persons working without pay, and rural areas are excluded. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreón, San Luis Potosí, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juárez, Tijuana, Matamoros, and Nuevo Laredo.

*Each of the coefficients presented is a percentage and is significant at the 1% level (returns to schooling).

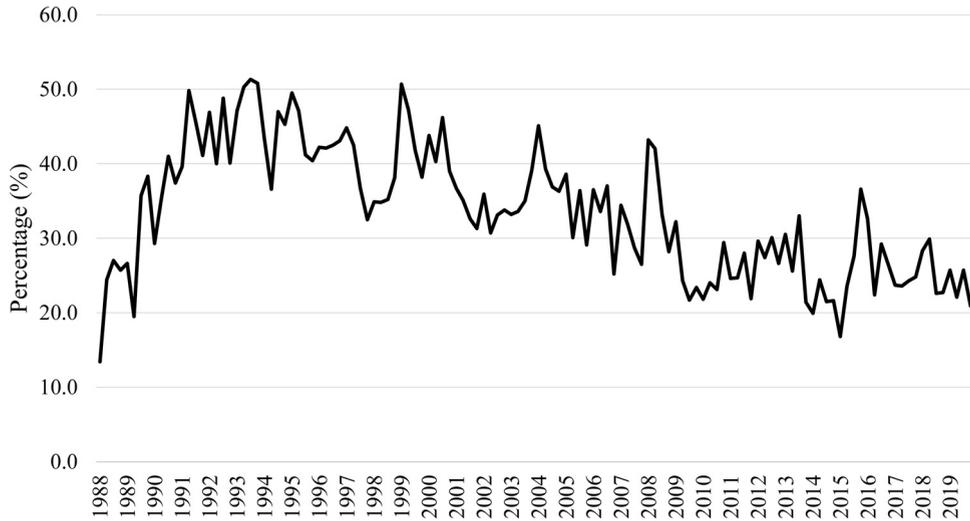


Fig. 7. Gender wage gap (self-selection biased), 1988:Q1–2019:Q4

Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo. *Each of the coefficients presented is a percentage and is significant at the 5% level.

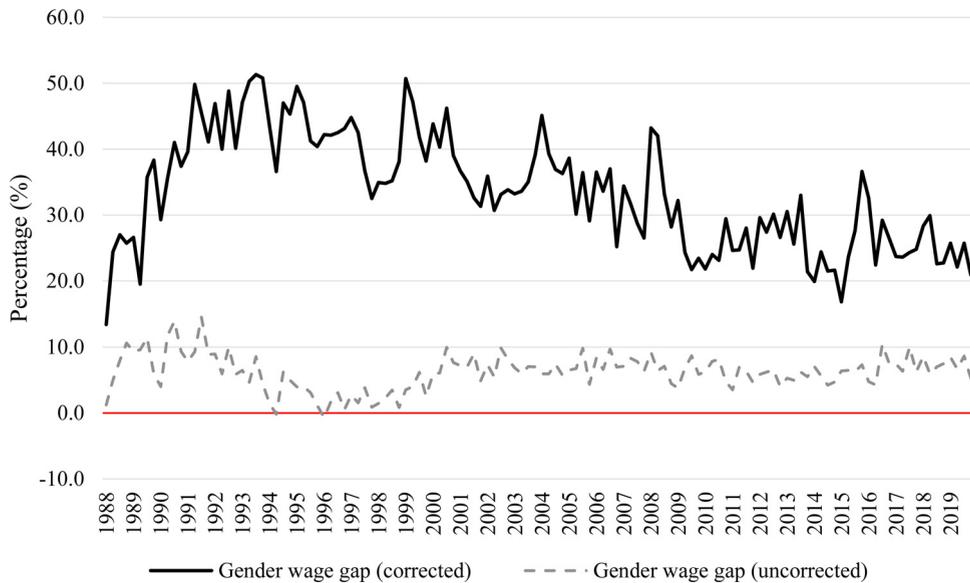


Fig. 8. Gender wage gap: the self-selection bias, 1988:Q1–2019:Q4

Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo. *Each of the coefficients presented is a percentage and is significant at the 5% level.

that the sum of these three effects results in the value of the gender wage gap. For example, if we were at the most recent point in the figure (2019:Q4), the endowment effect is -6.7 , remuneration is 24.4% , and interaction is 3.2% , resulting in a gap of 20.9% .

According to the last figure, two results should be clarified: (1) the selection bias effect represents 15.6% of the gap for this period, but this is absorbed in the three effects (endowment, remuneration, and interaction), without knowing which effect captures this self-selection bias in a more significant proportion, which is a methodological limitation. (2) The remuneration effect captures the residual effect. These two unobservable factors are detailed in the following section.

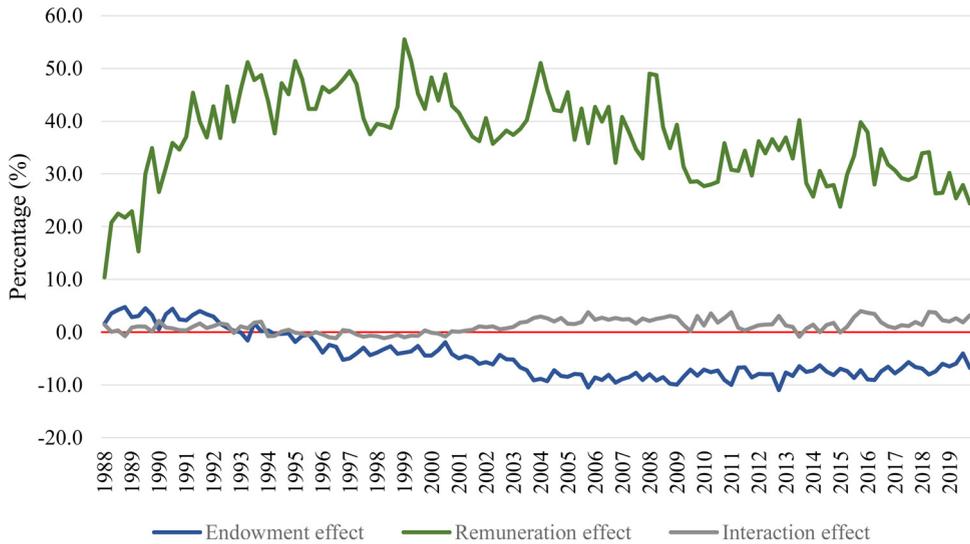


Fig. 9. Gender wage gap decomposition, 1988:Q1–2019:Q4

Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo. *Each of the coefficients presented is a percentage and is significant at the 5% level. Each of the reported effects already includes the correction for self-selection bias.

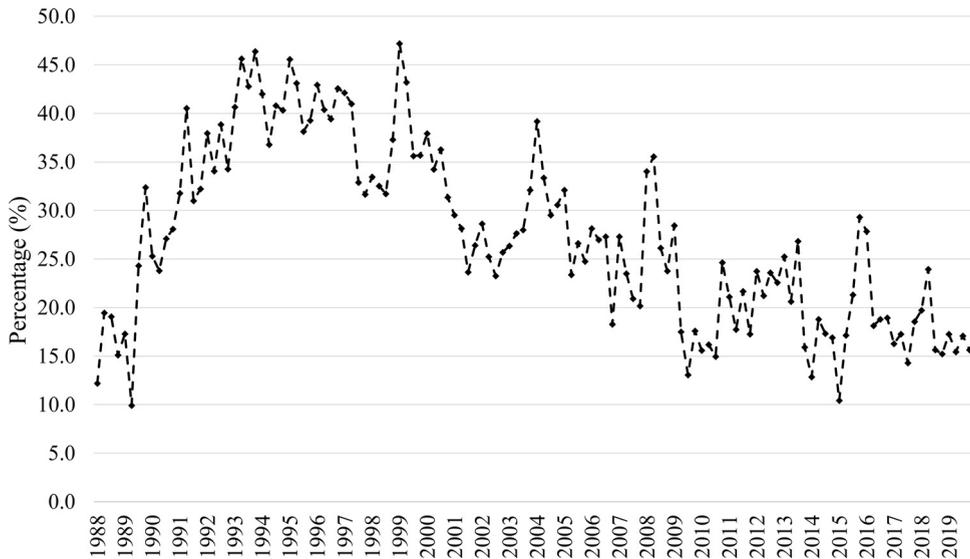


Fig. 10. Self-selection bias contribution to the gender wage gap, 1988:Q1–2019:Q4

Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo. *Each of the coefficients presented is a percentage and is significant at the 5% level.

5.3.2. The effects of latent variables (non-observable)

This last section presents the main contribution of our analysis, which is to deepen the understanding of the unobservable effects of the gender wage gap in the formal labor market. Fig. 10 shows the self-selection bias effect of the gender wage gap decomposition. This effect’s trend fluctuates around 27.4% throughout the period analyzed and is positive. Intuitively, the fact that self-selection bias is positive can be attributed to the decrease in women’s labor participation relative to that of men in proportion and characteristics

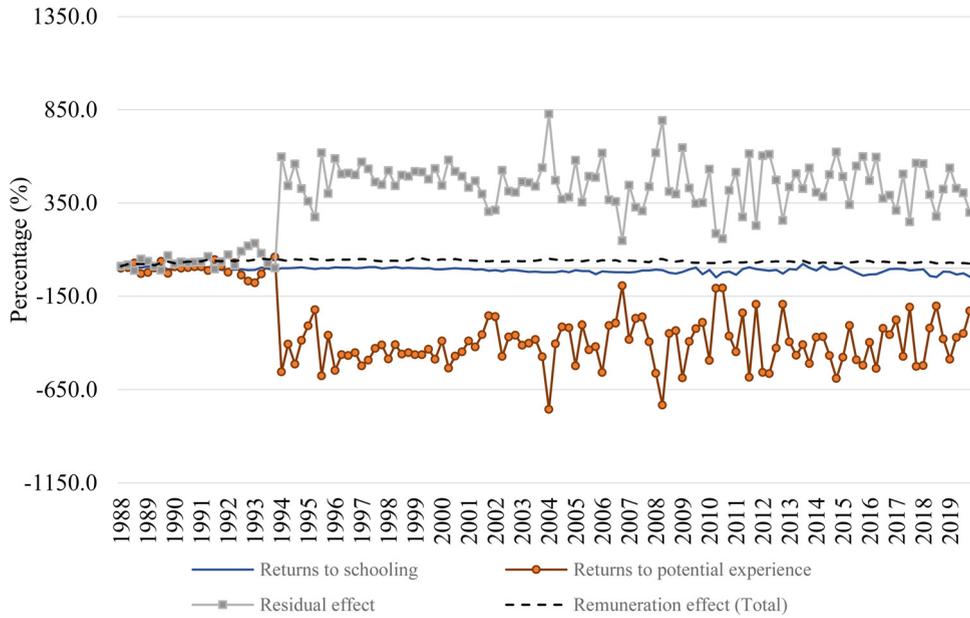


Fig. 11. Decomposition of remuneration effect, 1988:Q1–2019:Q4

Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo. *Each of the coefficients presented is a percentage and is significant at the 5% level. Each of the components and effects reported already includes the correction for self-selection bias.

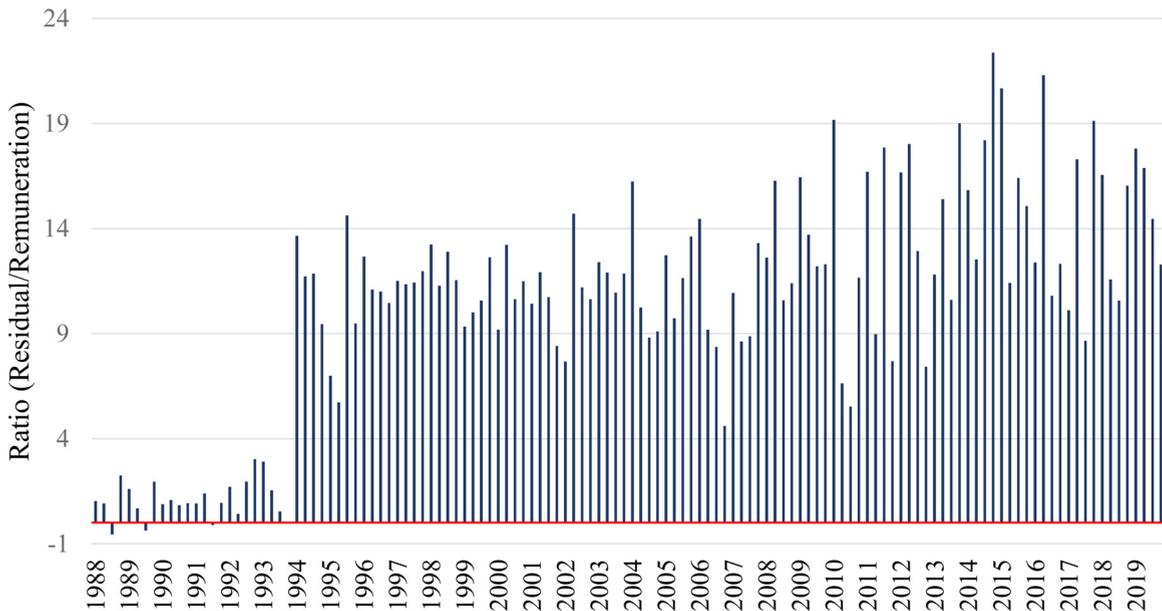


Fig. 12. Residual on remuneration effect, 1988:Q1–2019:Q4

Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo. *Each of the coefficients presented is a percentage and is significant at the 5% level. Each of the components and effects reported already includes the correction for self-selection bias.

that determine individuals' productivity in the market (e.g., education, work experience); as a consequence, relative wages decrease, and the gender wage gap widens (Mulligan & Rubinstein, 2008; Caamal, 2013).

Finally, we analyze what we call in this study the residual effect. We must remember that econometrically, the residual effect is estimated in a residual manner in the remuneration effect. For this reason, we believe it is pertinent to show this effect's behavior and contribution over time.

Fig. 11 shows the decomposition of the remuneration effect, which consists of three components: the returns to schooling, the returns to potential experience, and the residual effect. The magnitudes of the returns to experience and the residual effect have the opposite sign throughout the period analyzed. Thus, the difference between the total compensation effect minus the returns to schooling provides the residual effect (potential discrimination).

Fig. 12 presents more precisely the difference to which we refer. From 1988:Q1 to 2000:Q4, the remuneration effect in the gap was equivalent in some proportion to the returns to schooling, returns to potential experience, and the residual effect. However, by 2001:Q1, the residual effect represents a little more than 50% of the pay effect, which is why in our research, we limit ourselves to calling it that, because this effect may be capturing omitted variables and market structures, not just what is attributed to "potential discrimination."

Given that this effect represents ten times the remuneration effect over the last three decades, it translates to almost 30% of the wage gap in the pro-amendments over this period. Therefore, it is worth noting that the unobservable effect that continues to dominate in magnitude is the "self-selection bias."

6. Conclusions

One of the most critical ways central banks can contribute to a country's development agenda is to focus their research on policy design to understand the relationship between inflation targeting and welfare. For decades, the complex links between inflation, economic growth, and welfare have been known. However, it is essential to analyze them in depth using the tools that other areas of knowledge can contribute to this research agenda, such as informational wealth and the diversity observed in the labor market as a basis for study.

This study deepens the analysis and estimation of the returns to average schooling and the gender wage gap for the formal labor market, identifying observable and unobservable effects in a historical and micro-founded context. This consistency in constructing the databases, variables, and micro-econometric estimators provides a historical-comparative context for the gender gap, which is the main contribution of our analysis.

We used the basic model Mincer (1975) proposed to estimate the returns to schooling, integrating the correction based on Heckman's (1977) seminal work, and used it in multiple contexts and studies. From these estimates, we propose an extension to the Blinder (1973) and Oaxaca (1973) model with an extension to the selection bias correction as in Mulligan and Rubinstein (2008). This extension to the gap decomposition allows identifying the observable and unobservable effects of gender wage differentials through integrating micro-founded time series for more than three decades. Thus, we use micro-econometrics: we estimate cross-sectional micro-founded models and construct a standardized time series for Mexico's formal labor market.

Our results show decreases in the average returns to schooling for both genders in the last two decades of the period analyzed, even though the average years of schooling have increased. In addition, the formal market has valued women more than men in relative terms since 2001. On the other hand, the gender wage gap has prevailed positively and significantly for more than 30 years, with unobservable effects (selection bias and the effect attributed to discrimination), confirming the existence of these differences.

The implications of our analysis allow us to deepen the understanding of gender differences from an economic context in line with new areas of research that highlight the complex relationship between inflation and employment. For example, Braunstein and Heintz (2008) find that women bear a larger share of the unemployment cost associated with policies whose ultimate goal is to control inflation.

Thus, promoting public policies that eradicate these gender gaps without distorting the structure and reallocation of decisions and factors of economic agents in the market is undoubtedly one of the most significant challenges of economic policies, and it is where the proposed line of research and the results found in this research will be of great relevance for central banks. In particular, the reduction in the gender gap could represent an increase in women's relative labor participation. Consequently, there could be a potential increase in society's productivity and welfare once we consider the returns to schooling and other market factors.

Finally, some of the future lines of work derived from using this micro-econometrics approach would allow studying the gender differences in formal and informal employment. In addition, to make an extension to integrate the cycles between unemployment, formal employment, and informal employment, researchers should seek to deepen the study of the heterogeneity of both genders and sectors of the economy, as some authors have done for Mexico (Alcaraz & García, 2006; Alcaraz et al., 2011; Levy, 2018; Escobedo & Moreno, 2020; Maloney, 2004; Moreno 2007; Moreno & Cuellar, 2021).

In this way, this work constitutes an effort to pave the way for many new research studies that take advantage of the wealth of information from complex databases at the individual level, in light of advances in economic science, thus providing valuable tools in designing public policies that consider the complex relationships of each agent with the institutions where they interact and make decisions.

Declaration of Competing Interest

The views expressed herein do not necessarily represent those of the affiliated institutions. The authors declare no conflict of interest.

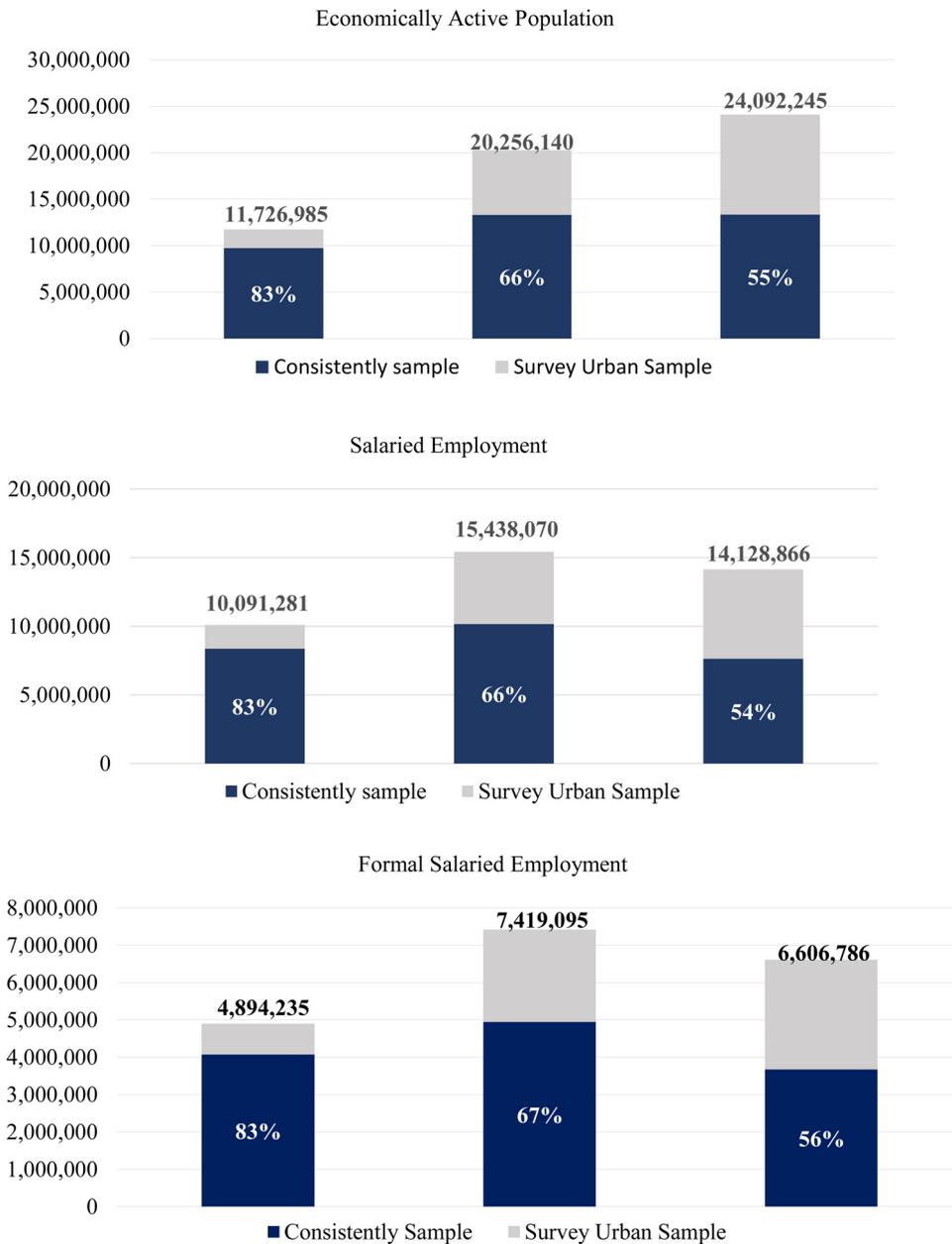


Fig. A1. Homologation of employment surveys for Mexico

Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019).

Appendix A

This appendix shows the composition of three main labor market categories: economically active population, salaried employment, and formal salaried employment. Figure A1 compares the subsample used in this research as a proportion of the entire employment in the survey.

Appendix B

Table B.1 presents the quarterly estimates of the returns to schooling based on the micro-founded models of the labor market and the market participation decision. The results are presented by gender, and a self-selection bias column is presented.

Table B.1
Estimated returns to schooling in Mexico's urban areas.

Year	Quarter	Women		Men	
		Returns	Self-selection bias	Returns	Self-selection bias
1988	I	5.8	10.1	6.1	-53.0
	II	5.9	11.8	6.1	-48.4
	III	6.5	9.1	6.7	-61.8
	IV	6.0	9.6	6.6	-66.8
1989	I	6.1	9.5	6.5	-60.2
	II	6.2	9.9	6.4	-49.5
	III	7.2	11.0	6.7	-72.3
	IV	7.0	15.4	7.0	-86.2
1990	I	6.6	15.0	7.3	-86.1
	II	6.6	9.0	7.2	-70.9
	III	6.8	10.5	7.7	-103.9
	IV	7.2	10.8	7.5	-101.2
1991	I	6.9	11.0	7.5	-105.6
	II	7.6	10.7	8.0	-104.1
	III	7.4	8.5	8.3	-100.4
	IV	8.0	16.9	8.1	-82.9
1992	I	7.8	16.0	7.9	-86.5
	II	7.6	13.1	7.9	-110.2
	III	8.2	7.6	8.0	-80.2
	IV	8.4	11.4	7.9	-61.3
1993	I	8.6	14.2	8.3	-73.3
	II	8.5	12.8	8.2	-74.7
	III	9.0	10.9	8.5	-74.2
	IV	8.8	23.7	8.3	-82.1
1994	I	9.4	13.7	8.9	-28.9
	II	9.1	14.4	8.7	-32.2
	III	10.0	10.2	9.2	-49.4
	IV	10.0	9.5	9.0	-35.5
1995	I	9.9	23.6	9.2	-47.8
	II	10.2	19.6	9.6	-41.3
	III	9.4	13.4	9.2	-55.1
	IV	9.9	18.0	9.6	-52.9
1996	I	9.9	16.9	10.0	-47.9
	II	9.8	11.8	9.7	-38.8
	III	9.7	19.6	9.7	-56.7
	IV	10.0	12.6	10.0	-56.6
1997	I	10.0	15.6	10.0	-47.5
	II	10.1	15.4	10.1	-38.8
	III	9.8	14.7	9.8	-57.4
	IV	11.3	16.9	10.2	-54.2
1998	I	10.1	18.3	9.8	-40.0
	II	9.8	21.2	9.8	-47.9
	III	10.0	17.9	9.8	-50.5
	IV	10.2	17.8	9.8	-36.8
1999	I	9.9	12.9	9.6	-45.9
	II	10.1	14.8	9.9	-54.3
	III	9.8	7.2	10.0	-51.6
	IV	10.0	12.7	9.5	-51.9
2000	I	10.0	12.6	9.6	-55.3
	II	9.8	13.7	9.5	-40.7
	III	9.8	11.0	9.3	-50.7
	IV	10.0	7.3	9.4	-43.0
2001	I	9.7	10.7	9.5	-25.2
	II	9.5	11.5	9.3	-27.0
	III	9.7	9.6	9.4	-32.5
	IV	10.0	12.6	9.2	-27.4
2002	I	9.7	17.4	9.1	-40.9
	II	9.6	12.6	8.9	-21.2
	III	9.5	15.4	8.9	-24.8
	IV	9.1	11.2	9.0	-20.2
2003	I	9.6	11.0	8.7	-19.5
	II	10.0	13.9	9.1	-25.7
	III	9.8	16.8	8.5	-40.4
2004	I	10.4	12.5	9.0	-23.6
	II	10.7	23.4	8.7	-33.4
	III	10.2	14.5	8.9	-26.9
	IV	9.3	14.6	8.4	-26.6
		9.2	11.2	7.9	-23.9

(continued on next page)

Table B.1 (continued)

Year	Quarter	Women		Men	
		Returns	Self-selection bias	Returns	Self-selection bias
2005	I	6.9	5.6	7.7	-28.5
	II	7.3	4.6	7.9	-37.9
	III	9.3	10.5	8.5	-36.1
	IV	10.5	13.4	6.9	-33.4
2006	I	10.3	14.4	9.0	-42.4
	II	9.9	12.6	7.6	-44.4
	III	9.9	17.5	7.4	-23.3
	IV	9.3	8.9	7.5	-27.4
2007	I	10.1	7.7	8.7	-44.9
	II	9.6	21.9	8.0	-53.5
	III	9.4	11.1	8.3	-53.0
	IV	10.3	7.1	8.5	-50.3
2008	I	10.0	13.1	8.6	-39.4
	II	9.6	23.7	8.6	-45.1
	III	9.6	9.9	8.4	-50.1
	IV	10.4	13.7	7.2	-27.4
2009	I	8.4	3.9	8.0	-57.0
	II	10.3	4.5	7.7	-46.0
	III	9.5	12.7	8.6	-47.4
	IV	8.8	11.3	8.1	-37.9
2010	I	8.1	10.1	8.8	-38.7
	II	8.8	21.8	8.0	-46.3
	III	8.4	15.5	8.1	-43.8
	IV	8.3	20.4	8.2	-48.3
2011	I	10.3	15.2	7.7	-45.8
	II	7.4	-0.7	8.4	-46.4
	III	9.1	4.5	7.9	-42.3
	IV	9.4	11.2	7.3	-29.0
2012	I	9.7	8.5	8.0	-22.0
	II	9.4	8.9	8.1	-41.8
	III	9.2	10.9	8.1	-51.7
	IV	10.0	19.7	8.2	-48.4
2013	I	9.0	17.9	7.8	-40.1
	II	9.7	13.1	8.1	-46.6
	III	8.0	2.7	8.0	-28.7
	IV	8.8	8.9	7.9	-36.3
2014	I	8.9	2.4	7.7	-25.3
	II	7.7	14.2	7.7	-52.0
	III	8.3	4.2	7.6	-35.8
	IV	9.3	7.1	7.6	-41.1
2015	I	8.5	4.7	7.1	-17.6
	II	8.7	1.2	7.3	-16.0
	III	9.9	0.3	8.5	-36.7
	IV	8.3	10.3	6.1	-29.6
2016	I	10.2	16.0	7.8	-52.1
	II	10.9	8.1	8.0	-46.8
	III	8.5	14.5	8.5	-33.2
	IV	9.2	16.5	8.6	-34.0
2017	I	9.6	19.0	8.3	-40.5
	II	9.6	10.4	8.4	-41.3
	III	8.9	5.7	7.7	-23.9
	IV	9.3	13.3	7.5	-40.7
2018	I	8.6	6.0	7.8	-49.8
	II	9.5	13.8	6.1	-36.2
	III	9.4	7.8	6.5	-24.4
	IV	7.2	2.1	7.0	-35.6
<i>(Continued)</i>					
Year	Quarter	Women Returns	Men Self-selection bias	Returns	Self-selection bias
2019	I	7.8	7.8	7.3	-18.0
	II	7.6	8.8	6.7	-32.3
	III	8.5	8.0	6.5	-20.6
	IV	9.2	17.0	6.1	-16.7

Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019). *Each of the coefficients presented is a percentage and is significant at the 1% level.

Appendix C

Table C.1 presents the quarterly estimates of the gender wage gap decomposition. The components of the gender wage gap, which explain the gender wage gap, are shown.

Table C.1
Gender wage gap decomposition.

Year	Quarter	Gender wage gap (corrected)	Gender wage gap (uncorrected)	Endowment effect	Remuneration effect	Interaction effect	Self-selection bias
1988	I	-17.8	13.4	1.2	1.6	10.4	-10.3
	II	-7.4	24.4	5.0	3.6	20.8	0.0
	III	15.9	27.0	7.9	4.2	22.5	19.5
	IV	-1.4	25.7	10.6	4.8	21.7	6.6
1989	I	5.2	26.6	9.3	2.8	22.9	14.0
	II	0.8	19.5	9.6	3.1	15.3	7.2
	III	9.5	35.7	11.4	4.6	30.0	16.6
	IV	13.6	38.3	5.9	3.3	34.9	25.2
1990	I	13.6	29.3	4.0	0.6	26.6	23.1
	II	13.6	35.5	11.7	3.4	31.2	16.5
	III	18.8	41.0	13.9	4.4	35.9	23.3
	IV	8.3	37.4	9.3	2.4	34.6	18.9
1991	I	18.2	39.6	7.8	2.2	37.1	30.5
	II	28.3	49.8	9.3	3.3	45.4	33.5
	III	21.3	45.5	14.5	4.0	39.9	25.1
	IV	23.4	41.1	8.9	3.4	36.9	36.4
1992	I	22.8	46.9	8.9	3.0	42.8	31.6
	II	29.1	40.0	5.9	1.6	36.8	38.9
	III	23.3	48.8	10.0	0.8	46.6	34.8
	IV	11.8	40.1	5.8	0.3	39.9	22.7
1993	I	29.7	47.1	6.5	-0.1	46.0	35.5
	II	27.0	50.3	4.7	-1.6	51.2	31.0
	III	23.4	51.3	8.5	1.7	47.8	26.0
	IV	28.6	50.8	4.4	0.2	48.7	46.2
1994	I	16.7	43.4	1.4	0.4	43.8	25.2
	II	29.9	36.6	-0.2	-0.4	37.7	39.2
	III	11.7	47.0	6.2	-0.3	47.2	21.4
	IV	20.3	45.3	5.0	-0.2	45.1	25.5
1995	I	49.5	3.9	-1.8	51.4	-0.1	45.6
	II	47.1	4.0	-0.7	48.0	-0.2	43.1
	III	41.2	3.1	-0.5	42.3	-0.6	38.1
	IV	40.4	1.1	-1.9	42.3	0.0	39.3
1996	I	42.2	-0.7	-3.9	46.5	-0.4	42.9
	II	42.1	1.7	-2.4	45.5	-1.0	40.4
	III	42.5	3.1	-2.8	46.4	-1.1	39.4
	IV	43.1	0.5	-5.3	47.9	0.4	42.6
1997	I	44.8	2.7	-5.0	49.5	0.3	42.1
	II	42.5	1.5	-4.0	47.0	-0.4	41.0
	III	36.7	3.8	-2.9	40.5	-0.8	32.9
	IV	32.5	0.8	-4.4	37.5	-0.6	31.7
1998	I	34.9	1.5	-3.9	39.5	-0.8	33.5
	II	34.8	2.3	-3.2	39.2	-1.1	32.5
	III	35.2	3.5	-2.7	38.7	-0.9	31.7
	IV	38.1	0.8	-4.1	42.7	-0.5	37.3
1999	I	50.7	3.5	-3.9	55.5	-0.9	47.2
	II	47.2	4.0	-3.6	51.5	-0.7	43.2
	III	41.8	6.2	-2.6	45.2	-0.7	35.6
	IV	38.2	2.5	-4.4	42.3	0.4	35.7
2000	I	43.8	5.9	-4.4	48.3	-0.1	37.9
	II	40.3	6.1	-3.4	43.9	-0.2	34.3
	III	46.2	9.9	-1.9	48.9	-0.8	36.3
	IV	39.0	7.6	-4.1	42.9	0.2	31.4
2001	I	36.7	7.2	-4.9	41.6	0.1	29.5
	II	35.1	6.9	-4.6	39.3	0.3	28.2
	III	32.6	9.0	-4.9	37.1	0.5	23.7
	IV	31.3	4.9	-6.0	36.2	1.1	26.4
2002	I	35.9	7.3	-5.7	40.6	1.0	28.6
	II	30.7	5.5	-6.1	35.7	1.1	25.3
	III	33.1	9.9	-4.3	36.9	0.6	23.3
	IV	33.8	8.1	-5.1	38.2	0.7	25.7

(continued on next page)

Table C.1 (continued)

Year	Quarter	Gender wage gap (corrected)	Gender wage gap (uncorrected)	Endowment effect	Remuneration effect	Interaction effect	Self-selection bias
2003	I	33.2	6.9	-5.2	37.4	1.0	26.3
	II	33.6	6.0	-6.7	38.5	1.8	27.6
	III	35.0	7.0	-7.2	40.2	2.0	28.0
	IV	39.1	7.0	-9.1	45.5	2.7	32.1
2004	I	45.1	5.9	-8.8	51.0	3.0	39.2
	II	39.3	5.9	-9.3	46.0	2.6	33.4
	III	36.9	7.4	-7.2	42.1	2.0	29.5
	IV	36.3	5.7	-8.3	41.9	2.7	30.6
2005	I	38.6	6.5	-8.5	45.5	1.6	32.1
	II	30.1	6.7	-7.9	36.5	1.5	23.4
	III	36.4	9.8	-8.0	42.4	2.0	26.6
	IV	29.1	4.4	-10.5	35.8	3.8	24.8
2006	I	36.5	8.3	-8.6	42.7	2.4	28.2
	II	33.6	6.6	-9.1	39.9	2.8	27.0
	III	37.0	9.7	-8.1	42.7	2.4	27.3
	IV	25.2	6.9	-9.5	32.1	2.7	18.3
2007	I	34.4	7.1	-8.9	40.8	2.4	27.3
	II	31.8	8.3	-8.5	37.9	2.5	23.5
	III	28.7	7.8	-7.7	34.7	1.7	20.9
	IV	26.5	6.3	-9.1	32.9	2.6	20.2
2008	I	43.2	9.2	-8.0	49.0	2.2	34.0
	II	42.0	6.4	-9.2	48.7	2.6	35.6
	III	33.2	7.1	-8.5	38.9	2.8	26.1
	IV	28.2	4.4	-9.8	34.9	3.1	23.8
2009	I	32.2	3.8	-9.9	39.3	2.8	28.4
	II	24.3	6.8	-8.5	31.4	1.4	17.5
	III	21.7	8.6	-7.1	28.5	0.2	13.1
	IV	23.4	5.8	-8.3	28.6	3.1	17.6
2010	I	21.8	6.2	-7.1	27.7	1.3	15.6
	II	24.0	7.8	-7.6	28.0	3.6	16.2
	III	23.1	8.2	-7.3	28.5	1.8	15.0
	IV	29.4	4.8	-9.1	35.8	2.7	24.7
2011	I	24.6	3.5	-10.0	30.8	3.8	21.1
	II	24.7	7.0	-6.7	30.6	0.9	17.8
	III	28.0	6.3	-6.7	34.4	0.3	21.7
	IV	21.9	4.6	-8.6	29.7	0.8	17.3
2012	I	29.6	5.9	-7.9	36.2	1.3	23.8
	II	27.4	6.2	-8.0	33.9	1.5	21.2
	III	30.1	6.5	-8.0	36.6	1.5	23.6
	IV	26.6	4.0	-11.0	34.5	3.1	22.6
2013	I	30.5	5.3	-7.7	36.9	1.3	25.3
	II	25.6	5.0	-8.3	32.9	1.0	20.6
	III	33.0	6.2	-6.4	40.2	-0.9	26.8
	IV	21.4	5.5	-7.5	28.3	0.7	15.9
2014	I	19.9	7.0	-7.3	25.7	1.4	12.9
	II	24.4	5.6	-6.3	30.6	0.0	18.8
	III	21.5	4.2	-7.5	27.6	1.4	17.3
	IV	21.6	4.7	-8.1	27.9	1.8	16.9
2015	I	16.8	6.4	-6.9	23.8	0.0	10.4
	II	23.6	6.5	-7.4	29.9	1.0	17.1
	III	27.6	6.3	-8.7	33.4	2.8	21.3
	IV	36.6	7.3	-7.2	39.8	4.0	29.3
2016	I	32.6	4.7	-8.9	37.9	3.7	27.9
	II	22.4	4.3	-9.1	28.0	3.4	18.1
	III	29.2	10.4	-7.4	34.7	1.9	18.8
	IV	26.4	7.5	-6.6	31.8	1.1	19.0
2017	I	23.7	7.4	-7.8	30.7	0.8	16.3
	II	23.6	6.3	-6.9	29.2	1.3	17.3
	III	24.3	10.0	-5.7	28.8	1.2	14.3
	IV	24.8	6.3	-6.6	29.5	1.9	18.6
2018	I	28.3	8.6	-6.9	33.9	1.4	19.7
	II	29.9	6.0	-8.0	34.1	3.9	24.0
	III	22.6	7.0	-7.4	26.3	3.7	15.6
	IV	22.7	7.5	-6.0	26.4	2.2	15.2
2019	I	25.7	8.4	-6.5	30.2	2.0	17.3
	II	22.1	6.7	-5.9	25.4	2.6	15.4
	III	25.7	8.6	-4.0	27.9	1.9	17.1
	IV	20.9	5.3	-6.7	24.4	3.2	15.6

Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU (1988–2000), ENE (2001–2004), ENOE (2005–2019).

*Each of the coefficients presented is a percentage and is significant at the 5% level.

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