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**EMPLOYMENT AND EARNINGS BY GENDER IN
MEXICO: ITS RELATIONSHIP WITH
TASK-BIASED TECHNOLOGICAL CHANGE**

**EMPLEO E INGRESOS POR GÉNERO EN
MÉXICO: SU RELACIÓN CON EL CAMBIO
TECNOLÓGICO SESGADO POR TAREAS**

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Resumen: To understand how employment and earnings by gender in Mexico are related to task-biased technological change, we analyze changes in employment by occupations defined by the tasks they perform. We also decompose the gender wage gap using the unconditional quantile regression method. The results indicate that the female labor market is polarizing and that the gender wage gap has fallen, but mostly within those occupations involving non-routine cognitive work. These changes have caused the gender wage gap to drop mainly in the upper part of the wage distribution, benefitting women with the highest levels of human capital.

Abstract: Para analizar el empleo y los ingresos por género en México y su relación con el cambio tecnológico sesgado por tareas, este trabajo presenta un análisis de los cambios en el empleo por ocupaciones definidas con base en el tipo de tareas que desarrollan. Además, presenta una descomposición de la brecha salarial por género mediante el método de regresión cuantílica incondicional. Los resultados indican que el mercado laboral femenino se está polarizando y que la desigualdad salarial por género ha caído, especialmente en las ocupaciones que involucran trabajo no rutinario cognitivo. Estos cambios han provocado que el diferencial salarial por género decrezca principalmente en la parte alta de la distribución.

Clasificación JEL/JEL Classification: J16, J31, O33

Palabras clave/keywords: salarios; diferenciales salariales por género; cambio tecnológico, México

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1. Introduction

Changes in labor markets around the world have been linked to structural changes such as trade liberalization, deregulation of economic activity, disincorporation of public companies, and liberalization of markets in general. However, technological advances are critical to understanding labor market changes.

Throughout history, different types of technological changes have occurred, and they have had various impacts on labor markets. For instance, on the one hand, Acemoglu (2002) states that the technology used in the Industrial Revolution during the eighteenth century replaced skilled work, which increased the demand for low-skilled workers. On the other hand, Acemoglu (2002) and Autor *et al.* (2003) mention that, as of the twenty-first century, the increasing use of IT systems and computers boosted the demand for highly educated employees.

Today, technological change seems to have a different impact, as it replaces employees who perform routine tasks, regardless of their skill level. Machines can now replace employees who perform tasks that follow clear rules. They also complement employees who perform tasks in which rules are not well established or systematically executed and cannot be coded by computers. This technological change has been called *task-biased technological change* (TBTC) and seems to be behind employment polarization seen in the United States, Germany, and the United Kingdom, among other developed countries.

The purpose of this paper is to link TBTC to gender labor differentials, using data from Mexico. For this, we created four occupation categories based on the type of tasks performed by workers: non-routine cognitive, routine cognitive, non-routine manual, and routine manual. Using these categories, we analyze changes in employment and labor income gaps by gender to understand whether wage differentials for women are smaller, or not, in either cognitive or manual non-routine occupations.

This kind of analysis enriches the literature that studies technological change's role in improving women's wages. For example, in the United States, the gender wage gap has decreased since the 1980s. Yamaguchi (2018) indicates that this relative improvement of women's wages has been attributed to higher educational levels in particular, and to investment in human capital in general. The author also states that attitudes towards women within the labor market have changed, which has led to less discrimination against them. However, the author considers that technological progress has been a critical factor in explaining this change. Other authors, such as Weinberg (2000), have

discussed this association, arguing that the decrease in the emphasis on physical work in labor markets and the increase in the emphasis on computer work has raised the female labor demand. Black and Spitz-Oener (2010) confirm that the shift in demand towards employees who perform analytical tasks and against employees who perform routine tasks, has produced favorable labor results for women.

Using the National Employment Survey (*Encuesta Nacional de Empleo*, ENE) and the National Survey of Occupation and Employment (*Encuesta Nacional de Ocupación y Empleo*, ENOE), Meza (2019) finds that female employment in Mexico has polarized in the same way that it has in highly developed nations. However, the male labor market has shown increased demand for workers who perform routine cognitive tasks. The author relates the first change to the occupational segregation of women in easily automated tasks, and the last change to the postponement of technological progress due to the prevailing low wages in the Mexican economy and the misallocation of resources that privileges less productive companies. The author speculates that international trade and offshoring have also had an impact on this result.

Based on data obtained from the ENE 2000 and the ENOE (2005 to 2017),¹ we find that the highest labor-based earnings in Mexico are obtained in non-routine cognitive occupations followed by routine cognitive occupations. Conversely, earnings from manual routine and non-routine occupations are quite similar, so employees are likely to move smoothly between these two types of occupations.

The results of our analysis indicate that the aggregate mean gender wage differential in Mexico has dropped slightly from 2005 to 2017 due to a decrease in the gender wage gap for those performing cognitive tasks. However, it has remained stable or decreased slightly for those employees performing manual tasks. This indicates that recent technological change has benefited women in Mexico. Furthermore, when breaking down the wage gap, it is found that most of it is not explained by the observable productive attributes of men and women, which suggests that behind our results are additional factors to education and work experience. We find a gender wage gap that indicates persistent discrimination against women in both 2000 and 2017. Nevertheless, it is worth mentioning that this discrimination element decreases as one moves towards the right-hand side

¹ The National Employment Survey was substituted by the National Occupation and Employment Survey in 2005. The National Occupation and Employment Survey is still conducted quarterly by INEGI.

of the distribution in 2000, and in 2017 occurs the opposite situation, since the discrimination component increases when approaching the extreme right-hand side of the salary distribution. This implies that the employees performing non-routine cognitive tasks - precisely those whom the advancement of technology has benefited the most - are those who are more adversely affected by discrimination during the period analyzed.

This paper is structured as follows. Section 2 shows a brief review of the literature that addresses the gender wage gap in Mexico. This section also discusses how technological change has affected the gender wage gap in other countries. Section 3 describes the data and methodology used in this study. Section 4 shows the results of the analysis and section 5 concludes.

2. Literature review

2.1. *The gender wage gap in Mexico*

The wage gap between men and women, as general gender differences in labor markets, have been extensively studied in both Mexico and the rest of the world. Studies have used different approaches, which provide a clear view of gender gaps worldwide. Since the 1990s, the gender wage gap has decreased throughout the world, which has been explained mainly by women's acquisition of higher education levels. Furthermore, the participation of more women in predominantly male occupations and industries has decreased occupational segregation and contributed to this fact (see Blau and Kahn, 1996; Weichselbaumer and Winter-Ebmer, 2003; Polachek, 2004, among others). Other factors such as market liberalization and technological change also contributed to this result. Moreover, several studies show that labor discrimination against women is now less frequent around the world.

Studies that analyze the gender gap in employment are classified into two broad categories. First, those aiming to understand the behavior of wage gaps over time and gender differences in labor markets, mainly by examining the supply factors behind these results. Second, those studies that analyze demand factors. Most of the studies in the first group were carried out in the 1980s and 1990s. In Mexico, examples of this type of studies include Pagan and Ulibarri (2000); Brown *et al.* (1999); García and Mendoza (2009); and Popli (2008, 2013), among others.

The supply factors that can explain the differentiated insertion of men and women in the labor market are -primarily- different educational levels, work experience, marital status, number of children, age, and race or ethnicity. These factors define the willingness to enter the market and the industries and occupations chosen, as well as the effort to work outside home. Studies that consider these factors use data from household surveys and decompose wage differentials to determine whether they are due to the characteristics of the employees themselves (observable characteristics), or to the prices that the market assign to each of these characteristics (unobservable characteristics). The varied decomposition methods are made either with mean data or data from the entire wage distribution, which has often led to conflicting results. Some of the studies related to these issues in other countries are those written by Light and Ureta (1995); Altonji and Blank (1999); Blau and Kahn (1996, 1997); Oaxaca and Ransom (1994); and Blau and Beller (1988). It should be noted that these type of analyses has been carried out in most countries worldwide. In general, a disadvantageous position among women is presented with signs of improvements.

On the other hand, a series of studies that, controlling for supply factors, focus on understanding if any demand factor has a different impact on the labor market for men and women. These studies have used household surveys and, more recently, company or firm-level surveys and censuses. Economic structural changes are among the demand factors that can modify the differentiated female labor insertion, such as deregulation, trade and financial liberalization, or disincorporation of public companies. Other factors that may be behind the differentiated changes in demand for men and women are business cycles, crises, or technological advances. Even demographic changes can create different working conditions for men and women. For example, in an aging society, women's opportunities may be more significant because of their ease in caregiving tasks. Some of the most relevant works in this group were written by Juhn *et al.* (2012); Aguayo *et al.* (2011); Domínguez and Brown (2010, 2013); Rodríguez and Castro (2014); and Rodríguez (2018, 2019), who analyze the Mexican case.

Finally, there is another group of studies that evaluate how labor market institutions, such as the minimum wage or unionization rates, affect labor participation of men and women in a different way, both in terms of supply and demand (Kidd and Shanon, 2002; Perugini and Selezneva, 2015; and Antonczyk *et al.*, 2010, among others).

In general, studies conducted in Mexico on gender differences in

the labor market have tried to include some demand factors in their estimates, especially since the country's economy began a process of openness and structural change. The work carried out by Alarcón and McKinley (1994) is a pioneer in this type of study. Using the National Survey of Household Income and Expenditure (*Encuesta Nacional de Ingresos y Gastos de los Hogares*, ENIGH) of 1984, 1989 and 1992, the authors analyze the gender wage gap in Mexico's urban area and relate it to the structural changes that the economy underwent over the studied period. The authors find that women earned 23.3% less than men did in 1984. That percentage increased to 28.4% in 1989, but decreased to 25.3% in 1992. By applying a Blinder-Oaxaca type decomposition on the gender wage gap, this work suggests that between 70% and 85% of this gap is associated with the different prices that the labor market assigns to men and women's characteristics. Therefore, they conclude that women would earn higher wages if they were paid according to men's earnings, which evidences discrimination. The study concludes that women should have benefited from the structural reforms, since a more competitive country rewards labor productivity and women tend to be more productive than men,² suggesting that other factors explain the misbehavior of the gender wage gap.

It is essential to mention that throughout the period analyzed by Alarcón and McKinley, other authors reported an increasing wage gap between highly-skilled and less-skilled workers in Mexico. Meza's study (2001) examines the Mexican context and performs a decomposition that shows an important factor behind the gender wage gap in Mexico: the skills wage gap, which is more significant for women between 1996 and 1998. The author finds that the gender wage gap decreased in Mexico between 1988 and 1996, either when measured with mean wages or when measured at different distribution points. However, this gap increases between 1996 and 1998, after an economic crisis. The study concludes that gender-specific factors promoted a gender wage gap reduction between 1988 and 1996. Furthermore, the study suggests that the female wage distribution was more affected by the skills wage gap, and that their returns to education were also higher than those of men. So this effect acts adversely during the period 1996-1998 (mainly in the lower part of the distribution) and explains the increase in the gender wage gap.

² This statement is controversial and is mainly associated with women's increased use of computers, which explains the greater return to education (see Meza, 2001).

Authors such as Campos-Vázquez (2013), Esquivel and Rodríguez (2003), and Rodríguez (2018), have found that the skills wage gap has decreased in Mexico since the mid-1990s due to trade liberalization and the growth of highly skilled labor in the country. However, technological changes have also accelerated in the first years of the twenty-first century. If structural reforms, *ceteris paribus*, benefit women in the labor market, we expect to find that technological changes generate greater demand for female labor. Therefore, we expect that the gender wage gap decrease, especially in occupations performing cognitive-type tasks between 2000 and 2017. The study of Juhn *et al.* (2012) addresses these issues. It develops a model where companies differ in productivity and employees are distinguished by their gender and level of qualification. According to these authors, a reduction in customs tariffs (associated to a wide trade liberalization) induces the most productive companies to modernize their technology and enter the export market. These new technologies involve computerized production processes and a lower need for physical skills of employees. As a result of this dynamic, women's relative wages and employment improve in blue-collar occupations, but not in white-collar occupations. This work contrasts its model with Mexican data taken from a firm survey indicating that companies involved with international markets tend to invest in cutting-edge technology and replace blue-collar male employees with blue-collar female employees. However, the results do not show that white-collar or highly skilled employees have also benefited in recent years from technology advances, a fact that our study demonstrates. Other authors such as Arceo and Campos-Vázquez (2014) find that in the upper section of the wage distribution in Mexico, the phenomenon of the *glass ceiling* is decreasing. This finding implies that well-positioned women in the Mexican labor market increasingly hold job positions of leadership and management. The authors conclude that Mexican women who enter the labor market are selected positively and that this selection is accentuated in the case of undereducated women and at lower quantiles.

2.2. *Technological change and the gender wage gap*

Most of the literature on the effect of technological advances on the female labor market in general, and the gender wage gap in particular, argues that new technologies benefit women since they shift the emphasis in jobs, from physical strength and manual ability, to analytical and interpersonal interaction skills, in which they tend to have a comparative advantage.

For example, Borghans *et al.* (2014) argue that interpersonal interactions are important in understanding individual job outcomes. Using data from the United States, the United Kingdom, and Germany, the authors find that jobs in which interpersonal relationships are more important employ higher female proportions. In terms of technological change, the authors point out that computerization and contemporary organizational working models complement interpersonal interactions, which generally benefit women. According to this study, the recent reduction in these countries' gender wage gap might be explained by a significant increase in the importance of interpersonal working tasks. The study conducted by Borghans *et al.* (2014) outlines in an incipient way a trend that seems to be happening worldwide, i.e., the outflow of employees from jobs that perform manual and routine tasks and the inflow into occupations that requires more analytical and public relations tasks.

This idea is confirmed by Black and Spitz-Oener (2010), who argue that closing the gender wage gap in developed countries has been attributed to supply factors, such as education and training, while demand factors have been neglected. To correct this bias, the authors analyze how the change in the tasks performed by men and women has affected the gender wage gap. The authors find that women have experienced more significant changes in the type of tasks they perform. Women have been transferred to a greater extent than men towards non-routine tasks, generating a massive outflow of women from occupations in which routine tasks are performed, while this outflow is not observed among men. This result is similar to what Meza (2019) finds for the case of Mexico: women have left routine-task occupations, while male routine-task occupations have increased. Black and Spitz-Oener (2010) demonstrate that the changes described reduced the gender wage gap.

In another study, Card and DiNardo (2002) assert that women are more likely than men to use computers in worksites, considering that complementarity with computer-based technology is measured by its rate of use. This fact has put upward pressure on female wages, which has reduced the gender wage gap.

A relevant aspect of the gender wage gap in developed countries such as the United States is that it has further reduced in large cities, where higher wages are also recorded when compared to those paid in smaller cities or rural areas. This means that women have an urban wage advantage over men. To find out if the reduction in the gender wage differential observed in the United States is related in any way to the urban wage premium, Bacolod (2017) uses data from

large metropolitan areas in that country for the years 2000 and 2010. This author argues that if men and women employ different skills when performing their jobs, and show different productivity in cities of different sizes, then it is foreseeable that different agglomeration forces will reward men and women differently. This study concludes, like those from other authors, that women focus on relatively more intensive jobs in interactive and cognitive skills, where technology is used more broadly. In contrast, men focus on jobs that are relatively more intensive in physical strength. Its decomposition analysis, which includes explanatory factors such as education, skills, and workplace location, predicts that women's wages will exceed men's in the aggregate. However, the study concludes that women benefit less from agglomerations, resulting in a gender wage differential in large U.S. cities.

According to the reviewed literature, women have greater cognitive and social skills than men, which suggests that if task-biased technological change rewards these abilities over physical ones, then they will benefit to the extent that technological advance is present in the country. An interesting hypothesis is that women and highly skilled employees have common skills, which proportionally increase their wages compared to those of other employees within an environment of radical productive change, such as the one promoted by the introduction of computers and digital platforms to the labor market. For example, a study conducted by Beaudry and Lewis (2014) found that the return for higher education has moved in a similar way but in the opposite direction as the change in the gender wage gap in the United States, i.e., while the return for higher education increases, the gender wage gap decreases. Based on data from 1980-2000, this article concludes that highly skilled employees and women have common job skills that have become more attractive in a work environment marked by information and communication technologies. However, given the period analyzed in this study, it is easy to conclude that technological change favors skills rather than non-routine tasks. Following their argument, it can be affirmed that if women have greater skills in non-routine tasks, they will benefit from the recent technological change.

The following section shows the data used in this study and the methodology used in its analysis.

3. Data and methodology

3.1. Data

The information used in this study was taken from ENE 2000 and ENOE 2005-2017, both carried out by the National Institute of Statistics and Geography (*Instituto Nacional de Estadística y Geografía*, INEGI). ENE conducted surveys of households from 1988 to 2004. From 2005 on, it was replaced by ENOE. This replacement had several objectives. First, by changing the reference period, it tried to make the measures of occupation, unemployment, and employment in Mexico comparable with those obtained in other OECD countries. It also sought to automate the survey processes, which until then had been manual. In addition, it made the subject matter of the new instrument broader and more relevant, improving its ability to identify phenomena commonly underestimated in surveys of this type, such as multi-employment and the population available to work. Finally, it expanded the offer of indicators to formulate labor policies. This implies that, although ENE and ENOE are not fully comparable, their measurements of wages and employment differentiated by sex are similar enough to make a comparative study covering the first 17 years of the twenty-first century. However, since we observed an increase in gender wage inequality in 2004 that we could not explain, we decided to analyze the gender wage gap using data only from ENOE (2005-2017).

Initially, ENE was conducted on an annual basis; however, since 2000 it was conducted continuously, and the results were published quarterly. On the other hand, ENOE is conducted quarterly. Both are representative of the population at the national and state levels, although ENOE is also representative at a city level.³

The data analyzed corresponds to the third quarter of each year. Annual samples were restricted to employees with a high commitment to the labor market, i.e., those who worked more than 30 hours per week before the survey and full-time employees.

Our study dealt with underreporting of earnings (see Rodríguez-Oreggia and López, 2015) by imputing labor income in the cases in which the interviewees refused to provide this information. The imputation procedure followed was that of hot deck, which is characterized by assigning a known or estimated value to those observations of missing data, using a vector of socio-demographic characteristics

³ Only for some metropolitan areas of the country.

(Rodríguez-Oreggia and López, 2015).⁴

Weighting factors were used in all estimates. Nominal labor income was deflated using the National Consumer Price Index so that it is expressed in constant terms (prices of 2017).

We classified all occupations from ENE and ENOE databases into the following categories: non-routine cognitive, routine cognitive, routine manual, and non-routine manual occupations, using either the Mexican Classification of Occupations (*Clasificación Mexicana de Ocupaciones*, CMO, valid until 2012) or the National Occupation Classification System (*Sistema Nacional de Clasificación de Ocupaciones*, SINCO, valid as of 2012). The main tasks performed in each one of the occupations of the unit groups were considered.

It is essential to mention that, in most cases, each SINCO unit group contained more than one occupation. Each occupation was classified into the groups mentioned based on the type of tasks performed. Once the SINCO classification was made, the CMO classification was developed using an equivalence table, where the same CMO group might host more than one SINCO unit group. To make the classification, the article conducted by Acemoglu and Autor (2011) was taken as a reference, where the groups were built based on the

⁴ The imputation process was as follows. First, a pool of observations was created with employed individuals, given that they had a job position such as subordinate and paid employees, employers, and self-employed workers. This was done for the four quarters of the year in question. Then, each one was assigned a random number between 0 and 1. A data set of donors (those with a declared income per work) and a recipient data set (those with non-declared income or with a declared range) were created from the pool. Recipients who reported less than a minimum wage were assigned the minimum wage multiplied by the random number already assigned. Those who declared a minimum wage were assigned this latter. A donor was found in the corresponding dataset for every individual who had not yet been assigned an income in the recipient dataset. More than one donor could be found, so the one with the highest random number (assigned when forming the pool) was selected. The tie variables for possible donors were as follows: sex, occupation condition, sector of economic activity (agricultural, manufacturing, commerce, services, and others), stratum, type of economic unit (companies, quasi-companies, private and public), and position in the occupation. Since it was almost impossible for donors with all tie variables to be found (more than 95% such donors were found), it was necessary to repeat the process three more times, but eliminating variables each time: first subsector, then subsector and stratum, and finally subsector, stratum and the type of economic unit, as long as it was different from “subsistence agriculture”.

following criteria (see table 1).

Following this classification of occupations and databases, in the next section, we present the methodology for analyzing changes in employment and wage gaps and an explanation of the unconditional quantile regression method used to calculate and decompose the gender wage gap.

Table 1
Occupational groups

<i>Groups</i>	<i>Definition</i>	<i>Example</i>
1.- Non-routine cognitive	To perform non-routine cognitive tasks, management skills, analytical reasoning, and quantitative skills such as arithmetic and advanced mathematics are required. Computers complement but do not replace human work. It includes tasks that require problem-solving skills, intuition, creativity, and persuasion.	Occupations that involve management, control and planning of activities requiring a high managerial and interpersonal level. (Medical diagnosis, sales, legal work). Professional, technical, and managerial occupations.
2.- Routine cognitive	Routine cognitive occupations require setting limits, tolerances, or standards, as an indicator since they follow precise and well-understood procedures.	To operate a billing machine to transcribe data from office records (Bookkeeping, archive/retrieve textual data, process interactions/ procedural transactions, for example, bank tellers).
3.- Routine manual	Routine manual jobs require ease of manipulation and organization in a systematic way.	Selection and classification of engineering objects on an assembly line, reconfiguring production lines to allow short runs. Employees in industrial plants.

Table 1
(continued)

<i>Groups</i>	<i>Definition</i>	<i>Example</i>
4.- Non-routine manual	Non-routine manual tasks are not subject to computerization. This means that they could not be easily replaced by a robot. They require situational, visual adaptability, language recognition and in-person interactions and have strong challenges to automation.	Occupations that imply ease for interpersonal relationships and decision-making at a basic level. Cleaning services, truck drivers, care providers, personalized attention in service locations.

Source: Own elaboration based on Acemoglu and Author (2011).

3.2. Methodology

To understand what has happened with male and female employment in the first 17 years of the twenty-first century, within the occupational categories described above, we present figures of changes in aggregate employment for the period 2000-2017. In addition, to understand these movements in detail, they are calculated with a disaggregation of age and level of education.

Subsequently, to find out what has happened with the gender wage gap over time, this gap is calculated using mean wage data and wage data at different distributional points. Additionally, to understand the gender wage gap changes throughout the distribution for the 2005-2017 period, gaps for the mean and the 10th, 25th, 75th, and 90th percentiles are calculated and shown in figure 4. These same wage gaps are then calculated for each of the occupations noted above.

We analyze the decomposition of the gender wage gap in Mexico by applying the unconditional quantile regression method developed by Fortin *et al.* (2011). The analysis is based on the idea that employees who perform non-routine cognitive tasks are located on the right-hand side of the distribution. In contrast, those who perform manual non-routine tasks are located on the left-hand side of the distribution. Different methodologies are available for conducting wage

decompositions, although most studies use the traditional Blinder-Oaxaca method (Oaxaca, 1973). However, in recent times both non-parametric methodologies, such as those of DiNardo *et al.* (1996), and parametric ones, such as that of Machado and Mata (2005) and Melly (2005) have been used for wage gap decompositions, in which an analysis throughout the entire wage distribution is performed (many of the studies also perform the Heckman Selection Bias Correction). Similarly, other studies have investigated those observable and unobservable factors that affect the wage gap (Juhn *et al.* 1991, 1993). Finally, the Nopo methodology (Nopo *et al.*, 2011) can be used to compare individuals with the same observed characteristics in each of the groups analyzed.

Fortin *et al.* (FLF, 2011) have proposed a technique for empirically estimating aggregate decompositions of differentials between distributions of a given variable. This technique provides a decomposition of differences that occur between the distributions at any point. In addition, it allows attributing the differences to both the observable characteristics and their prices. Finally, it allows estimation of the individual contribution of each explanatory variable considered in the analysis to the gap under study. The advantage of this technique is that it provides estimation of the aggregate decompositions of differences between distributions based on the construction of counterfactual distributions and diverse approximations, such as non-parametric approaches based on the re-weighting of the sample. In other words, the technique developed by FLF (2011) makes it possible to perform detailed decompositions and estimate the impact of changes in the endowments or the returns of a specific explanatory variable on the quantiles of interest of an unconditional distribution.

The FLF methodology (2011) is structured in two steps. The decomposition of a gender pay gap is developed as an example. The first step (following Firpo *et al.*, 2009) starts with the estimation of a Mincer equation, where the logarithm of the log hourly wage (dependent variable) is replaced by what the authors call the Recentered Influence Function (RIF). The RIF is obtained as a transformation of the original dependent variable, which shows the importance of each available observation of the independent variables in determining the dependent variable. The RIF's expected value is specified based on a linear approximation of the explanatory variables considered, such as personal characteristics (age, education, marital status) and employment characteristics (work experience and sector of economic activity). A RIF's regression is estimated for each of the logarithm's

quantiles of the hourly wage on the explanatory variables.⁵

$$RIF(W/Q_\theta) = Q_\theta + \frac{\theta - 1(W < Q_\theta)}{f_w(Q_\theta)} \quad (1)$$

Where Q_θ represents each of the wage distribution quantiles and f_w represents the complete wage distribution. In the process, the estimated coefficients are interpreted as the effect of an increase in the mean value of an explanatory variable on the Q_θ quantile of the distribution. As a second step, a standard decomposition of Blinder-Oaxaca (Oaxaca, 1973) on the log hourly wage differential is developed, when conducting the estimation through ordinary least squares. However, the decomposition is applied to each quantile, based on the estimates obtained from the RIF regression. The decomposition takes the following form:

$$\Delta Q_\theta = (\bar{X}^m - \bar{X}^h) \hat{\gamma}_{Q_\theta}^* + \{ \bar{X}^m (\hat{\gamma}_{Q_\theta}^h - \hat{\gamma}_{Q_\theta}^*) + \bar{X}^h (\hat{\gamma}_{Q_\theta}^* - \hat{\gamma}_{Q_\theta}^m) \} \quad (2)$$

Where ΔQ_θ is the difference at the Q_θ quantile of the wage distributions of female and male employees, and $(\bar{X}^m - \bar{X}^h)$ represents the difference in the mean of the observable characteristics between women and men. The second component of the equation is $\bar{X}^m (\hat{\gamma}_{Q_\theta}^h - \hat{\gamma}_{Q_\theta}^*) + \bar{X}^h (\hat{\gamma}_{Q_\theta}^* - \hat{\gamma}_{Q_\theta}^m)$ and represents the differences in prices between the two groups of employees, and of the characteristics of each type of employee (effect of coefficients). In other words, the differences in the coefficients not explained by the differences in the X observable characteristics of the different employees.

4. Results

4.1. Changes in employment by occupation and gender

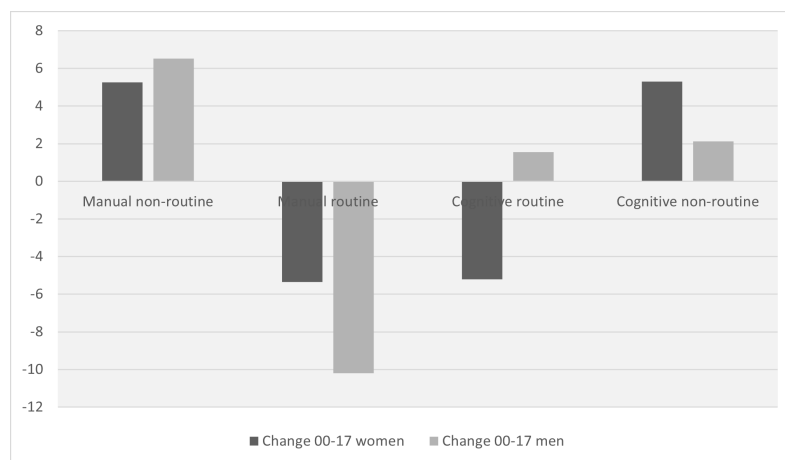
This section describes changes in male and female employment for each of the occupations of our interest, as well as changes defined by their age range and level of education. Estimates are made using data from ENE 2000 and ENOE 2017.⁶

⁵ In the original methodology, each quantile of the estimate is called the “unconditional quantile”.

⁶ The results of this section are the same if we use data from 2005 to 2017, as if we use only ENOE.

Figure 1 shows the relative change in male and female employment in occupations defined by the type of tasks they perform between 2000 and 2017. The results indicate that both women and men have increased their participation in occupations where non-routine cognitive and manual tasks are performed. However, in the case of men, they have also increased their participation in occupations performing routine cognitive tasks. This clearly indicates polarization in female labor market. Indisputably, female participation in routine occupations has fallen in the analysis period. More men than women have entered occupations performing manual non-routine tasks, while more women than men have entered occupations performing cognitive non-routine tasks.

Figure 1
*Relative change in employment of women and men
by type of tasks from 2000 to 2017*



Source: Own elaboration based on data from ENE and ENOE corresponding years.

Figure 2 shows the change of women's relative employment concerning men in different age ranges and for each of the types of tasks that we described above. This information corresponds to the period 2000-2017. When the indicator is positive, it means that women's employment, relative to men, has increased in that age range.

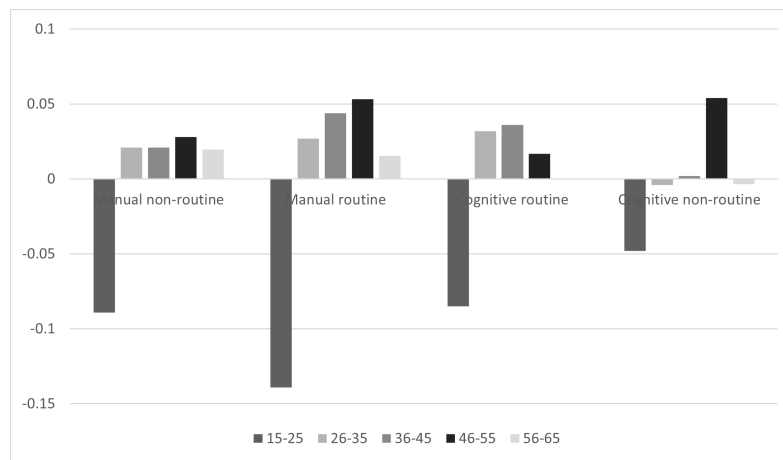
A first result to be highlighted is that relative female employment has grown more than men's in almost all age groups and at

least in three of the occupation groups. This is the result of the overall increase in female labor participation in the analysis period. A second interesting result is that female labor participation decreased for the 15-25-year age group for the four occupation groups analyzed, suggesting that younger generations of women are staying longer in school.

As shown in figure 2, women have reduced their participation in non-routine cognitive occupations in all age groups, except in the group of 46-55 years. This fact is worth highlighting since it suggests that women entering occupations that perform cognitive non-routine tasks are mainly older women with more work experience. In routine cognitive occupations, the participation of women increased compared to men in the age ranges of 26-35, 36-45, and 46-55, in contrast to the groups of younger (15-25) and older (56-65) women. Finally, in non-routine and routine manual tasks, women's participation increased in all age ranges except the youngest (15-25 years).

Figure 2

*Change in relative employment of women
(relative to men) in age ranges by type of
tasks from 2000 to 2017*



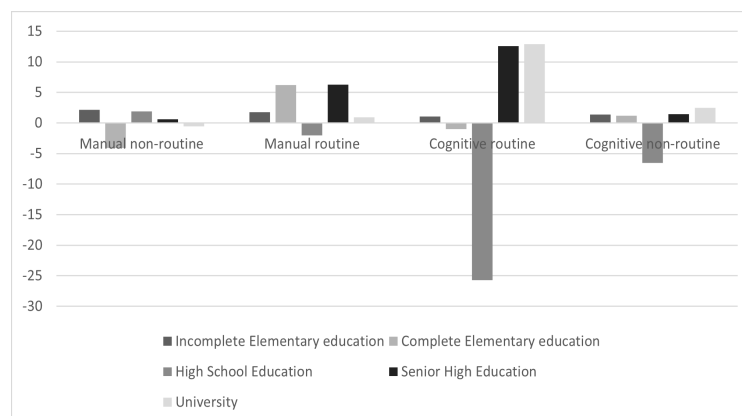
Source: Own elaboration based on data from ENE and ENOE corresponding years.

Figure 3 shows the change in relative female employment concerning men in different schooling categories by type of tasks performed. This information corresponds to the period 2000-2017. As

seen in the previous case, if the indicator is positive, it means that women's employment, concerning men, has increased in that education range.

Figure 3 reveals that women with a high school or a university-level education, employed in cognitive occupations, whether routine or non-routine, have increased their participation in employment relative to men. At the same time, those who did not study past high school have decreased their participation in this category. In fact, it is interesting to see how this group - women who did not study past high school - appear to have moved into job occupations that perform non-routine manual tasks. The size of the bars also suggests that women in this group who have not been able to obtain jobs that perform cognitive tasks have chosen to decrease their labor participation. Figure 3 also shows that women without instruction have increased their participation in both routine and non-routine manual tasks.

Figure 3
*Change in relative employment of women
(relative to men) in educational levels
by type of tasks from 2000 to 2017*



Source: Own elaboration based on data from ENE and ENOE corresponding years.

In brief, this section of the paper finds evidence of polarization in the Mexican female labor market. It is also observed that male employment increases in occupations performing routine cognitive tasks. This result goes hand in hand with the evidence found by Meza (2019)

in Mexico since it has been documented that women have increased their participation in occupations where they perform non-routine tasks, whether manual or cognitive.

When analyzing the change in relative female employment -relative to men- in different age ranges and educational levels, within the occupations defined by the type of tasks performed from 2000 to 2017, we found that women between 26 and 55 years increased their participation in most occupations. This result is related to the increase of female labor force participation. On the one hand, women between 46 and 55 increased their labor participation in non-routine cognitive tasks. We also found that women who had completed a higher educational level have increased their labor participation in most occupations, mainly in non-routine and routine cognitive jobs. On the other hand, women without instruction and with only a high school education level have increased their participation in jobs performing non-routine manual tasks.

Turning to the question of whether the gender wage gap has changed as women's employment has, we develop below an analysis of the gender wage gap, considering the different types of tasks performed.

4.2. *The gender wage gap in Mexico in the 2005-2017 period*⁷

To understand what happened to the gender wage gap in Mexico between 2005 and 2017, table 2 shows estimates of the log hourly gender wage differentials, both in their mean values and for four different points of the distributions. The results of table 2 are presented in figure 4.⁸

⁷ To avoid a full comparison over time of wages obtained using two different surveys (ENE and ENOE), we decided to use only ENOE data in this section of the paper.

We analyze labor income and not wages, but to simplify terms, we refer to gender wage gaps.

⁸ The same figure was elaborated with data from the period 2000-2017. It showed an increase in the gender wage gap in 2004, which we attributed to the change in the survey. However, the data in 2000-2003 was very much consistent with the tendency of the gender wage gap in the following years. This is why we decided to perform the complete decomposition analysis comparing 2000 and 2017.

Table 2
The gender wage gap in Mexico, 2005-2017

<i>Year</i>	<i>Mean</i>	<i>P10</i>	<i>P25</i>	<i>P75</i>	<i>P90</i>
2005	0.07	0.13	0.15	0.05	0.00
2006	0.06	0.09	0.11	0.02	0.04
2007	0.04	0.10	0.07	0.03	0.00
2008	0.07	0.11	0.10	0.05	0.02
2009	0.04	0.07	0.06	0.00	-0.04
2010	0.06	0.13	0.12	0.02	0.00
2011	0.05	0.12	0.11	0.00	-0.02
2012	0.05	0.08	0.07	0.02	-0.03
2013	0.03	0.05	0.06	-0.01	-0.03
2014	0.02	0.00	0.06	-0.01	-0.03
2015	0.03	0.07	0.11	0.01	-0.07
2016	0.06	0.14	0.08	0.00	0.04
2017	0.05	0.12	0.12	0.01	-0.04

Source: Own elaboration based on ENOE corresponding years.

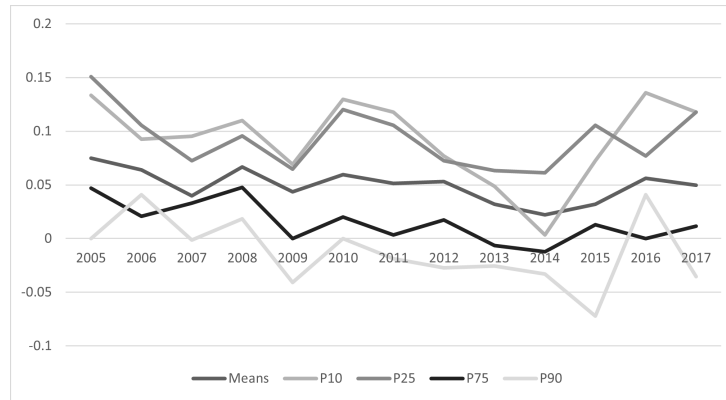
The data in table 2 shows that, during the 2005-2017 period, the gender wage differential is more significant in the 10th and 25th percentiles of the distribution than in the upper part. In fact, the differential decreases as we move to the right of the distribution. This suggests that in the years between 2005 and 2017, the most qualified and better-remunerated women enjoyed more equality.

As shown in table 2 and figure 4, the mean gender wage gap decreased slightly during the period analyzed (from 0.07 to 0.05). However, the gender wage gap fell more in the upper part of the distribution, while it decreased less in the lower part.

Indeed, figure 4 clearly shows how the gender wage gap falls in the 90th and 75th percentiles of the distributions in 2005-2017, which suggests that women placed at the top of the wage distribution have benefited more from the labor changes of the first years of this century. The figure also shows that the gender wage gap dropped in 2009, after the 2008 economic crisis, which could have caused unemployment and loss of wages for men and women. What can we say about the type of tasks that employees perform at different points of the wage distribution? Table 3 shows the mean monthly wages,

in 2017, for the different types of tasks that we have been discussing and by gender. Clearly, the highest wages are earned in occupations that perform non-routine cognitive tasks, followed by those earned in jobs performing routine cognitive tasks. Finally, wages in manual jobs, both routine and non-routine, are very similar, suggesting that less-skilled employees move smoothly between these two types of occupations.

Figure 4
Gender wage differentials in Mexico from 2005 to 2017



Source: Own elaboration based on data from ENOE corresponding years

Table 3
*Mean monthly wages by type of occupation
and gender, 2017*

	<i>Men</i>	<i>Women</i>
Non-routine cognitive	14,005	10,011
Routine cognitive	8,563	6,839
Routine manual	6,155	4,546
Non-routine manual	6,221	4,554

Source: Own elaboration based on ENOE corresponding years.

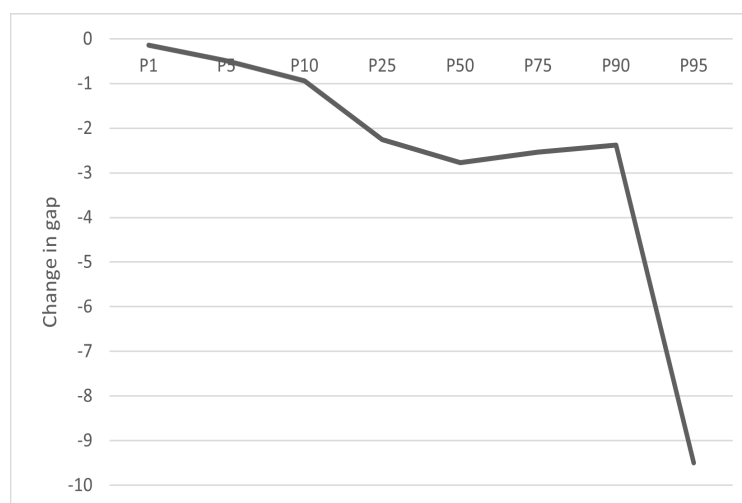
Cognitive work involves complex decision-making and mental processes rewarded by the labor market over other tasks, while employees performing manual tasks earn a lower income, which puts them at the bottom of the wage distribution.

The data contained in table 2 and figure 4 suggest that women who perform both routine and non-routine cognitive work increased their wages compared to men, decreasing the gender wage gap in the upper part of the wage distribution more than in other points of the distribution. This is consistent with the idea that women have a comparative advantage in cognitive tasks. On the other hand, women who perform manual work, both routine and non-routine, experienced a smaller increase in wages than men, which led to a slight decrease in the gender wage gap's lower part of the wage distribution.

4.3. Gender wage gap by percentile and type of tasks

To understand how the gender wage differential behaves in the period of analysis, 2005-2017, figure 5 shows the change in the gender wage gap between these years throughout the distribution. Inequality drops more at the top of the distribution and less at the bottom.⁹

Figure 5
Gender wage gap in Mexico from 2005 to 2017, by percentile



Source: Own elaboration based on data from ENOE corresponding years.

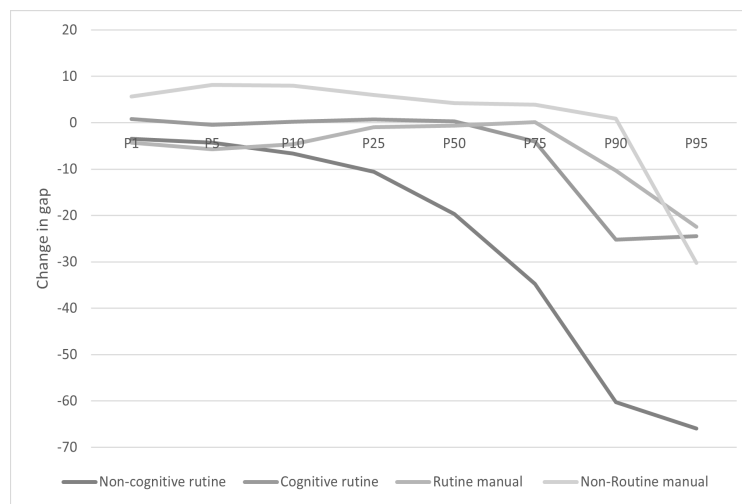
⁹ This result does not change if the figure depicts the changes between 2000 and 2017. However, the 2005-2017 figure is located below the 2000-2017 figure, such that the gender wage differential decreases slightly in the 10th percentile of the distribution. This figure is available upon request.

This part of the study shows the results obtained when analyzing the gender wage gap by type of tasks from 2005 to 2017. First, we present evidence of the gap's changes throughout the distribution for each type of tasks analyzed, and then we make the decomposition by quantile for the years 2000 and 2017.

The results of figure 6 suggest that, in the study period, inequality falls in all occupations but drops more in those that perform non-routine cognitive tasks. This drop is more noticeable in the upper part of the distribution, although it happens even in the middle and lower parts. In routine occupations, both cognitive and manual, as well as in non-routine manual occupations, the drop in inequality is only observed at the upper part of the distribution.

Figure 6

Gender and occupational wage differential from 2005 to 2017



Source: Own elaboration based on data from ENOE corresponding years.

The results suggest that the wage differential by gender in Mexico would be greater in the upper and the middle part of the distribution if there were no drop in inequality in non-routine cognitive tasks. In fact, the fall observed in figure 5 can be attributed to what happens in non-routine cognitive occupations.

Based on the literature analyzed and the results obtained, we suggest that in Mexico, as in other countries, women show a comparative advantage in non-routine tasks, and especially in non-routine

cognitive tasks. If this is true, it implies that task-biased technological change benefits women in terms of employment and wages or labor income. It is important to note that the drop in the gender wage inequality in occupations performing routine tasks is observed above all in the highest part of the distribution. This suggests that women with higher levels of human capital, i.e., higher education and work experience, are the ones that are obtaining better remuneration. In contrast, women with lower educational levels are moving towards non-routine manual jobs, where wages have not improved much relative to men.

After analyzing these results, it is essential to review in detail the wage differentials by gender and their decomposition throughout the distribution, to see whether the inequality and its decomposition are the same in the upper, middle and lower percentiles. In addition, it is relevant to understand what part of the wage differential is due to disparities in observable productive characteristics and what part is due to differences in the prices assigned to each of these characteristics. Finally, the analysis of the following section allows us to understand which variables explain the gender wage differences.

4.4. Gender wage differential and its decomposition with the unconditional quantile regression methodology

We applied the unconditional quantile regression method to obtain the gender wage differential and its decomposition in Mexico between 2000 and 2017 throughout the distribution. We do this to know what part is due to observable production characteristics and what part is due to changes in prices and determine which variables contribute the most to this explanation. We assume that employees performing non-routine cognitive tasks are located on the right-hand side of the distribution, and those performing non-routine manual tasks are located on the left-hand side. Table 4 shows the results of the decomposition exercise, which includes the logarithm of hourly wages for men and women, the differential, and the decomposition of wage inequality.

The data in table 4 are presented in figure 7, which shows the gender wage gap and its decomposition throughout the distribution for the years 2000 and 2017. The figure reveals the contribution of the observable productive characteristics in logarithmic terms (explained part) and the differences in the prices of those characteristics (unexplained part). A positive value indicates that it is a favorable indicator for women.

The results show that the logarithm of the women's hourly wage is less than that of men in both years and throughout the distribution, which implies a negative differential in all the points analyzed. We also found that, in 2000, the wage differential in benefit of men decreases as one moves to the right-hand side of the distribution, which suggests that women performing manual tasks suffer more inequality than those performing cognitive tasks. In 2017, we observe that the differential in benefit of men also decreases as one moves towards the highest part of the wage distribution, which is consistent with the finding that the gender wage differential in the aggregate decreases throughout the distribution between 2000 and 2017, favoring women who perform cognitive tasks.

By breaking down the gap, we show that both the explained part and the unexplained part of the differential decreases in 2000 as we move to the right-hand side of the distribution, indicating that women performing manual tasks suffered greater discrimination at the beginning of this century. In contrast, this discrimination is higher in the upper part of the salary distribution in 2017. That is, the unexplained part of the differential grows as we move to the right-hand side of the distribution.

It is notable how the explained part of the gender wage differential is positive in almost all the points of the analyzed distribution, both in 2000 and in 2017, so it benefits women. In the samples, women have higher levels of human capital than their male counterparts, suggesting that discrimination is behind their lower wages. However, it is remarkable that the explained part of the differential, in 2000, decreases as one moves along the distribution towards occupations performing cognitive tasks. This is contrary to 2017 when the explained part increases as we move to the right-hand side of the distribution, suggesting that women performing cognitive tasks receive higher remuneration because of their higher levels of human capital. This is consistent with previous findings that suggest that women with higher levels of human capital are gaining positions and breaking the *glass ceiling*, as they are being inserted in occupations performing non-routine cognitive tasks.

Regarding the discriminatory component (unexplained part of the differential), table 4 and figure 7 show that this is higher in manual occupations in 2000 but higher in cognitive occupations in 2017. This implies that, in 2017, women performing cognitive tasks suffered from greater discrimination than women who performed manual tasks. This fact is striking since female wages increased the most for those performing cognitive tasks.

Table 4
Results of the wage decomposition exercise for Mexico from 2000 to 2017

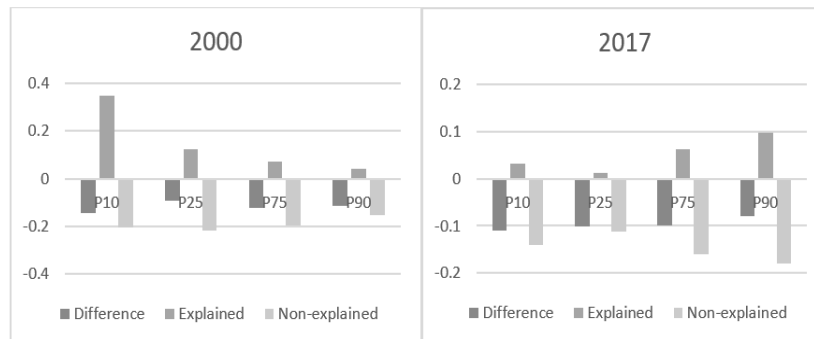
	<i>2000</i>				<i>2017</i>			
	P10	P25	P75	P90	P10	P25	P75	P90
Log H	2.232***	2.635***	3.551***	4.162***	2.500***	2.881***	3.655***	4.072***
EE	[0.0113]	[0.00727]	[0.00939]	[0.0124]	[0.00923]	[0.00595]	[0.00766]	[0.00954]
Log M	2.088***	2.727***	3.674***	4.275***	2.609***	2.982***	3.755***	4.152***
EE	[0.0109]	[0.00509]	[0.00546]	[0.00856]	[0.00669]	[0.00372]	[0.00455]	[0.00722]
D	-0.144***	-0.0917***	-0.123***	-0.113***	-0.109***	-0.102***	-0.0996***	-0.0800***
EE	[0.0157]	[0.00888]	[0.0109]	[0.0150]	[0.0114]	[0.00702]	[0.00891]	[0.0120]
Exp	0.325***	0.0876***	0.0315***	0.00359	0.00867	-0.0122***	0.0410***	0.0780***
EE	[0.0137]	[0.00677]	[0.00849]	[0.0119]	[0.00721]	[0.00427]	[0.00615]	[0.00858]
No Exp	-0.181***	-0.179***	-0.155***	-0.116***	-0.118***	-0.0895***	-0.141***	-0.158***
EE	[0.0179]	[0.00996]	[0.0106]	[0.0161]	[0.0127]	[0.00750]	[0.00895]	[0.0140]
Cons	0.737***	-0.179***	-0.155***	-0.116***	0.266***	0.0184	-0.187***	0.130*
EE	[0.127]	[0.00996]	[0.0106]	[0.0161]	[0.0718]	[0.0404]	[0.0518]	[0.0737]
OBS	164,706	164,706	164,706	164,706	118,925	118,925	118,925	118,925

Notes: Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own estimates based on data from ENE 2000 and ENOE 2017, third quarter.

Figure 7
Wage decomposition by gender, 2000-2017

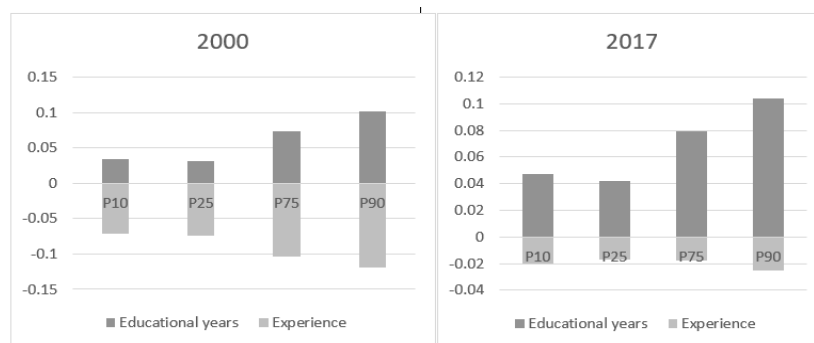


Source: Own elaboration based on data from ENE and ENOE, respective years.

The decomposition through the RIF allows us to analyze the individual contribution of each of the explanatory variables contemplated in the model to the change in the gender wage gap. A positive value of the coefficients indicates that this explanatory variable increases wage inequality (i.e., benefits men), and a negative value indicates that it reduces wage inequality (i.e., benefits women). The explanatory variables included in the decomposition correspond to the years of education and work experience. Figure 8 shows that education generates an increase in the gender wage gap across the distribution, mainly in the high-wage group in 2017. In other words, it appears that men are better rewarded for education than women, while the opposite happens with experience, which benefits women.

Therefore, the results suggest that the gender wage differential in Mexico would be more significant if there were no bias benefitting women's analytical work, mainly in occupations where non-routine cognitive tasks are performed. These results coincide with Yamaguchi's findings (2018) regarding the changing nature of occupations in developed countries and the benefits implied for women. In Mexico, the results also suggest that work experience and women's commitment to the labor market are being rewarded above all. Another striking result is the increase in the discriminatory component of the gender wage differential, which contradicts a global trend.

Figure 8
*Decomposition wage gap explained by education
 and experience from 2000 to 2017*



Source: Own elaboration based on data from ENE and ENOE, respective years.

5. Conclusions

The objective of this paper was to analyze the effect of *task-biased technological change* on the gender labor differentials within the Mexican labor market. When analyzing employment, there is evidence of increased female job prospects in both cognitive and manual non-routine tasks, and male job opportunities performing both non-routine and routine cognitive tasks. These results suggest that technological change is a more relevant force in the female labor market, while trade or offshoring seem to be more relevant forces in the male labor market.

The paper shows that older women (46-55 years) are increasing their participation in occupations that perform cognitive tasks, while women who only completed high school are moving to occupations performing non-routine manual tasks.

When analyzing the wage gender gap, the results are interesting. First, we found that women earn less than men in all occupations defined by the type of tasks they perform, although inequality decreases as remuneration increases. Second, we identified that the discriminatory component towards women increased in the first years of this century, mainly in the upper part of the distribution, and that women's work experience is the most contributive factor reducing the gender wage gap.

Numerous studies have analyzed the effect of trade openness and technological change on the gender wage gap in recent years. However, few studies address this research problem through a percentile analysis for Mexico. This paper contributes to the literature and shows that Mexican women perform better in occupations where non-routine cognitive tasks are executed. As shown mainly at the top of the distribution, Mexico's gender wage gap does decrease thanks to the strong effect of women in occupations performing non-routine cognitive tasks.

The results suggest that women better complement current technology. However, there is a part of the wage differential that is not explained by the observable characteristics of the workers (the discriminatory component), which seems to explain the wage gap more than the observable characteristics. This is notable mainly in non-routine cognitive occupations in 2017 (for example, those occupations located in the highest part of the distribution) and suggests that if discrimination did not exist, women would have benefited even more from the labor changes that technology has brought about.

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