UNIVERSIDAD AUTÓNOMA DE NUEVO LEÓN
FACULTAD DE ECONOMÍA
DIVISION DE ESTUDIOS DE POSGRADO

"ESSAYS ON GENDER ECONOMICS AND THE MEXICAN LABOR MARKET"

Por

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Tesis presentada como requisito parcial para obtener el grado de Doctorado en Ciencias Económicas

Febrero, 2023

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UNIVERSIDAD AUTONOMA DE NUEVO LEON
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To my dear and loving wife

“Your words are my guide, your light is my motivation, and your love will always be my strength to continue my path.”
– C –

Acknowledges

I would like to acknowledge and give my thanks to my principal advisor, Dr. Jorge O. Moreno Treviño, who made this work possible. His guidance, consistent support, and friendship carried me through all the stages of my Ph.D. program and the start of my career as an economist.

I would also like to express my appreciation to my committee members, Dr. Joana Chapa, Dr. Ernesto Aguayo, Dr. Harry Patrinos, and Dr. Laura Juárez, for their valuable suggestions and interest in the revision of this work.

Likewise, I would like to thank the wonderful people in the Faculty of Economics at the Universidad Autonoma de Nuevo Leon, especially Dr. Pedro Villezca and Nancy Moreno, who always supported me in my career as a doctoral student. Also, I am grateful to all my professors who trained me in my career as an economist.

Thanks to the Consejo Nacional de Ciencia y Tecnología (National Council of Science and Technology) for the financial support for my studies.

To all of you, thank you very much.

Dedication

I would like to dedicate this work to my parents, Cecilia and Miguel, who always instilled in me the values and tenacity necessary to succeed. In addition, my sister, Angela, has always been my motivation and strength to take every step I take.

I would also like to dedicate this great goal to those who played an excellent role as parents and as the most loving grandparents in this universe, Rafael and Laura. Where each one of them is, there will be my heart.

Also, I would like to thank the rest of my family, who were always in the sound and not-so-good moments.

Of course, thank you very much to my friends, who have come a long way in my life and have become my family, Ana and Xhunashi. I would also like to thank my friend, colleague, and confidant, Lia, who, with her friendship, enthusiasm, and collaboration, has been part of this adventure (called "doctorate") with me.

To the great people who have been part of this journey, who, with their skills and teachings, have contributed more than they believe in my path, Dr. Aleida Nuñez, and Dr. Diana Vazquez, thank you very much for everything.

Moreover last but not least, I would like to dedicate this achievement and every one of them to the love of my life, my wife, Bianca. Who, with her love, patience, tolerance, and affection, has been part of this. This achievement is as much hers as it is mine because it would have been more challenging without her. Also, I want to thank her for giving me one more family, whom I thank for always being there, Magie, Jesus, Karla, Karen, Jesus R., and our nephews Renata and Frank Carlo. We love you, and you are always in our hearts.

Dear love, this is just the beginning of our dreams and goals. Thank you, infinite!

Table of Content

List of tables

List of figures

INTRODUCTION

The Mexican labor market is one of the most interesting markets but also one of the most complex to analyze. Labor informality, skills mismatch, and incentives based on the endogenous decision to work are just some of the issues that make Mexico one of the countries to analyze for those specializing in labor economics. In addition, the history of labor economics in Mexico became interesting after the COVID-19 pandemic because the labor market dynamics responded differently in each component group.

This dissertation comprises three research articles in labor economics. Specifically, it analyzes the gender decomposition of the Mexican labor market historically and studies the impact on the labor market derived from the most recent pandemic, COVID-19. Some variables of interest in this work are average schooling, real wages, returns to schooling, gender wage gaps, and labor supply.

Although there are many studies on the Mexican labor market, one of the main contributions of this work is to have constructed homologous and comparable data for the last thirty years in Mexico. This database is based on the country's public employment surveys. This data allowed us to have a photograph that shows the history of the Mexican labor market.

Regarding the theoretical framework of the chapters, the first chapter studies the labor market from a human capital perspective (Becker, 1954), endogenous labor market decisions (Heckman, 1977), and wage gaps (Blinder, 1974; Oaxaca, 1974 & Mulligan and Rubistain, 2008). On the other hand, the second and third chapters share the same theoretical framework, which is based on a short-run neoclassical general equilibrium model (Arrow et al., 1969).

For all the research, we use the standardized quarterly labor market databases from the existing employment surveys for Mexico: the National Urban Employment Survey (ENEU), the Employment Survey (ENE), and the National Occupation and Employment

Survey (ENOE). Given that the harmonized aims to achieve a comparable and consistent sample over time, all rural areas of the country are excluded. In addition, we only work with the formal market from 16 to 65 years. Moreover, the sample only contains the following metropolitan areas, which have been in the sample since the first quarter: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo.

This introduction is aimed at summarizing each of the chapters developed. Chapter 1, *"Employment, wages, and the gender gap in Mexico: evidence of three decades of the urban labor market"* studies the historical evidence of the gender gap in employment and wages in Mexico. This work uses standardized information and consistent estimates based on labor supply and a human capital approach. To achieve that, we construct consistent time series from 1988:Q1 to 2019:Q4 using employment surveys in Mexico. For the estimation, we used a model of labor participation in the formal market and wages for each gender on the formal market, correcting the corresponding selection biases. Based on these results, implement a Blinder-Oaxaca (1973) decomposition based on Mulligan and Rubinstein (2008) to estimate the gender gap in wages, identifying the importance of the selection bias. Our results suggest that the returns to schooling for both genders have decreased in the last two decades, showing a gap in returns to schooling in favor of women of around 2% in recent years. The gender wage gap fluctuates around 29.6% once the self-selection bias is corrected. The prevalence of differences in expected wages between gender exists due to the positive magnitudes of the "selection bias" and "residual" effects. The main limitation of this work is that it focuses only on formal urban employment in 16 metropolitan areas in the surveys for the three decades studied. However, this makes it possible to identify long-term trends and structural changes over time in these markets. The results demonstrate the importance of the interrelationships between economic agents and their decisions in the market, particularly the participation in formal labor employment.

Chapter 2, *"Employment, gender gap, and the Mexican industry: the effect of covid-19 on the dynamic structure and recovery in the labor market"* analyzes the impact of the

COVID-19 pandemic on the dynamics and recovery of the Mexican labor market, identifying the economy's employment by industrial sectors and gender. Using the Mexican urban employment surveys, the research identifies consistent micro-founded time-series from 1993:Q1 to 2021:Q4 and estimates a Vector Autoregressive model (VAR) linking aggregate production and each market segment. The results suggest significant adverse effects on employment resulting from the COVID-19 crisis for females and males. There are diverse employment losses and recoveries across different industrial segments suggesting a critical structural change in the market resulting from the pandemic. The sectorial-gender employment effects present a lower forecasted response to the initial shock but substantial observed employment losses, potentially linked to changes in the market structure. The complexity of this crisis entails crafting policies to enhance job recovery while promoting gender equality in the market.

Finally, chapter 3, *"COVID-19, formal employment by skill segment and the gender gap in Nuevo Leon: dynamic and persistent effects in the labor market"* estimates the depth and persistence of the first economic shock (I-shock) due to COVID-19 pandemic on the dynamics of formal employment in Nuevo Leon, segmenting employment by labor skills and gender. In this work, we build consistent micro-founded time-series from 1987:Q1 to 2020:Q1 using the Mexican urban employment surveys. Aditionally, we estimate a VAR model linking the sectorial regional economy and the labor market, using the Indicador Trimestral de la Actividad Economica Estatal (ITAEE) and each labor market segment. Our results suggest that High-skill employment is elastic to COVID-19 economic I-shock, but recovery is faster, while low-skill employment is the opposite. High and low-skill female employment increased, which reduced the relative gender gap. This multidimensional crisis suggests crafting policies to invest in human capital to have a high-skill labor market and achieve gender equity. Some limitations include the exclusion of informal employment and rural areas of Nuevo Leon, which allows us to recover long-run regional employment trends.

The principal contribution is first regional study to recover the employment structure by skill-gender, and estimate the loss and potential recovery of employment resulting from the shock of COVID-19 pandemic.

CHAPTER I. Employment, wages, and the gender gap in Mexico: evidence of three decades of the urban labor market[1]

1.1 Introduction

The labor market is a crucial element for achieving economic growth in any country globally, so knowing its structure allows us to identify 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, gender wage gap, sociodemographic characteristics such as age and sex are examples of observables structural problems. On the other hand, unobservable ones include motivation, persistence, delayed gratification, grit, and other non-cognitive abilities that are typically not observed. These problems directly impact the development of countries, and emerging economies are the most affected due to the barriers generated by these structures (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, Chiquiar, and Ramos-Francia (2008) show that informal employment is a structural problem of the Mexican labor market and 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 the reallocation of workers in the labor market between formal and informal employment.

These structural deficiencies negatively impact economic growth and can be cushioned by central banks, which play a crucial role in guaranteeing economic and financial stability through monetary policies aimed at maintaining stable prices (IMF, 2021). Although the main objective of central banks is to keep inflation low, studying market structures is essential for these institutions since these structures can indirectly interfere in their

[1] Published paper: Cuellar, C., & Moreno, J. (2022). Employment, wages, and the gender gap in Mexico: evidence of three decades of the urban labor market. Latin American Journal of Central Banking, 3(2), 100055. http://dx.doi.org/10.1016/j.latcb.2022.100055

monetary policies through the potential output gap, which is a crucial variable for the estimation of the interest rate (Guisinger, Owyang & Shell, 2018).

For this reason, analyzing structural components of the economy 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 will allow the design of appropriate public policies to correct them, 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 riches of the various employment surveys conducted in Mexico for more than three decades. We have called this time series approach based on micro-founded estimates because it combines the microeconometric 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 whole sample period, making the estimates comparable over time. Second, quarterly estimates of the cross-sectional type are made, and with this, 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 observable and unobservable components of the gap, the selection bias of the wage gap, among others. Having these series allows us to understand the historical picture on a continuous basis, 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, so our objective is not to identify the differences as a result of "potential discrimination," but to analyze it from a more profound approach, where not only 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 harmonized 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 by presenting the implications of the results obtained.

1.2 Labor participation, monetary policy, and structural labor market barriers

1.2.1 Potential female labor force participation

The labor market comprises a set of interactions between economic agents, and these simultaneous interactions generate structures that are not always efficient, as is the case of gender differences in the labor market. Gender differences in the labor market can be measured through indicators such as labor participation or observed wages, which are limited metrics for attributing gender differences since there are observable factors (education, marital status, age) and unobservable factors (preferences for leisure, use of time, skills) that are correlated with the existence of gender gaps (Cuellar & Moreno, 2021). Nevertheless, analyzing observed variables, such as women's potential labor participation, can show us the magnitude of the problem in the deficiency of labor structures such as returns to schooling and gender wage differentials.

Table 1.1 shows the descriptive statistics in proportions of women who are economically inactive in Mexico but who could potentially be part of the labor market since 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 are 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 are within the productive age range to generate maximum income (26 to 55 years).

Table 1.1 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

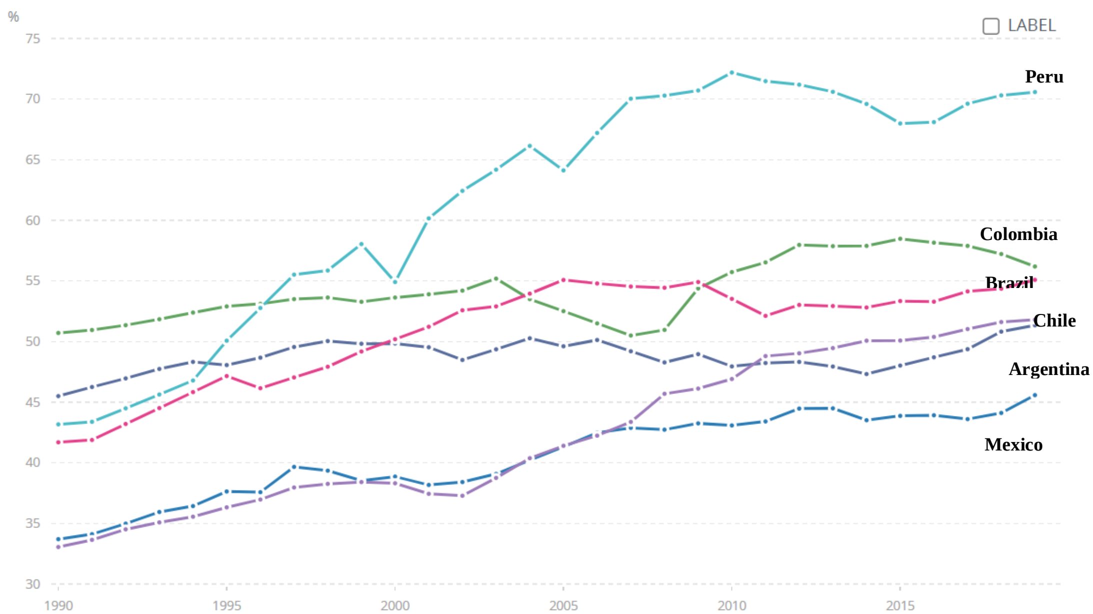
Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU(1988-2000), ENE(2001-2004), ENOE(2005-2019).

The composition of the PLFPR in the last three decades has remained stable; 25% are female students while 75% are female housewives. 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 (INEGI, 2020). This situation generates deficiencies in female employment labor structure, so understanding why these women are not working can be a starting point. One of the reasons women decide not to work may be that about 75% of the PLFPR are women with at least one child, which may represent a barrier to entry into the market.

Finally, Table 1.1 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, which is reflected in the low percentage of labor participation of women in Mexico compared to other emerging economies in Latin America such as Argentina, Brazil, Chile, Colombia, and Peru (Figure 1.1).

According to data from the International Labor Organization (2021), female labor participation in Mexico is the lowest among emerging economies in Latin America. The most recent data for Mexico, 2019, shows that, on average, women represent 45.8% (Figure 1.1). 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 Colombia, already in the 1990s, its female labor force represented 50.71% of the labor market, while it was only 33.7% for Mexico.

Figure 1.1 Labor force participation rate, female (% of female population ages 15+) (modeled ILO estimate) - Mexico, Colombia, Argentina, Brazil, Peru, Chile



Source: World Bank (2021)

This indicator, according to economic theory, 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), especially for central banks, since understanding the structure of the market would allow them to make better decisions if it is a bank whose objectives include maintaining long-term economic stability.

1.2.2 Monetary policies and their relationship to labor market structures

The main objective of central banks is to conduct monetary policy to achieve price stability (low and stable inflation). In some developed economies, stabilizing policies are also sought to reduce the output gap (IMF, 2021).

One of the primary keys to achieving a stabilizing policy is the method of measuring the output gap, and 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 structural barriers of the labor market and its components (e.g., gender differences in potential labor participation, returns to schooling, and gender wage gaps), they could use these microfoundations to set more effective monetary policies.

Currently, there is no single theoretical method for measuring the output gap, and this complicates policy decisions for central banks, especially for low-income ones, since deviating from the main objective (keeping the inflation rate low and stable) may generate discrediting of their monetary policies (IMF, 2015).

Guisinger, Owyang, and Shell (2018) study six different 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 measure used by the Congressional Budget Office (CBO) is a model 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 the case of Mexico, which, since it does not have a dual mandate in its policies, the estimation methodology used is more deterministic, using the Hodrick-Prescott (HP) filter[2] with tails correction to estimate the output gap, and generates an estimation of bands which use the methodology of unobserved components (Harvey, 1990).

The accurate estimation of the output gap implies that central banks can also have more efficient policies, since, 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.

So, once we understand the link between the implicit relationship between existing structural barriers to labor market entry and monetary policy decisions, we should not lose the focus of this study which is the micro-founded structural analysis of these market barriers.

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

Analyzing labor market deficiencies has its complexities, as 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.

The gender wage gap has been a topic on which many researchers have contributed various papers for 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, Pagan and Rodriguez (1999), Martinez and Acevedo (2004), Popli (2013), Arceo and Campos (2014) and, finally, Castro, Huessca, and Zamarron (2015) have conducted studies on the wage gap and labor participation in Mexico. The importance of discussing the works of these authors lies in the methodology used to address these issues since most of them differ in the methodology employed.

[2] The Hodrick-Prescott filter is a data-smoothing technique. HP filter decomposes the time series in two components: tendency and cycle.

Brown, Pagan, and Rodriguez (1999) use Wellington's decomposition (1993) to explain the differences between gender wage gaps and report that investment in human capital during the period 1987 to 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, and some occupational categories were overrepresented too. 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, this is later controlled by occupation.

Martinez 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 85% of discrimination is the effect of the wage structure. In comparison, the other 15% is explained by the higher marginal productivity of women than men, which is not reflected in the salary received.

Popli (2013), Arceo and Campos (2014), and Castro, Huessca and Zamarrón (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, which he uses 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, he finds that women's percentiles are relatively higher than 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 evolution of the wage gap in Mexico from 1990 to 2010. For their analysis, they use the 1990, 2000, and 2010 Population and Housing Censuses, in addition to 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 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, Huessca, and Zamarrón (2015) conducted a study for Mexico's northern border, finding significant wage differences between men and women. Furthermore, after correcting for selection bias using the methodology proposed by Heckman (1977), their estimators were more robust, having a difference of at least 2% compared to their estimators without correcting for selection.

Based on the previous literature, there are several methodologies to estimate gender wage gaps. Some emphasize the importance of correcting for selection bias, while others only seek to find differences at two different points in time. For this reason, the main contribution of this research 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, and thus capture the structural behavior based on the trends of the estimates. Furthermore, an extension to the model proposed by Blinder (1973) and Oaxaca (1973) 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.

1.3 Data

1.3.1 Sources of information

For the analysis, we standardized three existing employment surveys conducted by the National Statistics and Geography Institute (INEGI): 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 microfoundations of the labor market.

INEGI collects the ENEU, the ENE, and the ENOE to capture data on employment and sociodemographic characteristics in Mexico. The first two surveys are the predecessors of the current ENOE.

These surveys have the particularity of being a rotating panel, in which 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 payment greater than zero, thus excluding individuals who work without receiving any payment or remuneration and individuals who work in the informal sector.

Regarding the definition of formal employment, we adhere to the definition of our previous research (Moreno and Cuellar, 2021), where for the case of salaried workers, we refer to whether the person has social security (IMSS or ISSSTE)[3]. 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.

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

Given that one of our main research contributions is the harmonization 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), in order to reduce the inclusion bias since these metropolitan areas are maintained in all surveys over time, this may seem to be a limitation of our work. However, it should be noted that these 16 metropolitan areas represent almost 70% of urban employment in the entire country throughout the period analyzed (see Appendix: Figure A.1). Finally, we exclude all rural areas for harmonization purposes since the ENEU only includes urban areas in Mexico.

1.3.2 The labor market in México: descriptive statistics

Section 2.1 showed the low labor participation of female employment for Mexico, but this behavior persists for the aggregate market. Table 1.2 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.

Table 1.2 Labor market statistics

	Shares (%)					
	First decade (1989-1998)		**Second decade (1999-2009)**		**Third decade (2010-2019)**	
	Total	**Urban**	**Total**	**Urban**	**Total**	**Urban**
Economically Active Popultation	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).

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

Specifically for Mexican women, the picture becomes murky in terms of labor participation, since over the last three decades, the representation is 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.

For the female labor force, four characteristics stand out: age, marital status, family status, and human capital (Table 1.3). Over the three decades, more than 50% of the female labor force comprises women between 26-55 years of age, this being the productive labor cycle. On the other hand, regarding the marital status of the labor force, about 30% of the women are married, highlighting the status of the free union, which had an increase in its composition of about 70% in the last decade. Regarding family status, on average, 15% of women are heads of households, and more than 90% of them have at least one child.

Finally, human capital is one of the main characteristic components of the labor market, and here women have shown substantial increases in it. In the last decade, 16.64% and 20.96% of women have a bachelor's degree nationwide and in urban areas. In addition, in the last decade, in urban female employment, only 2.31% have no education whatsoever, so that human capital is a component of heterogeneity in the labor market for women, which is why it is of interest to study it.

1.3.3 Formal employment, schooling, and real wages: a historical analysis of the structural barriers for the woman to enter the labor market

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 not only allows us to capture the long-term trend behavior but also to identify the evolution of gender differences in wages, education, and employment.

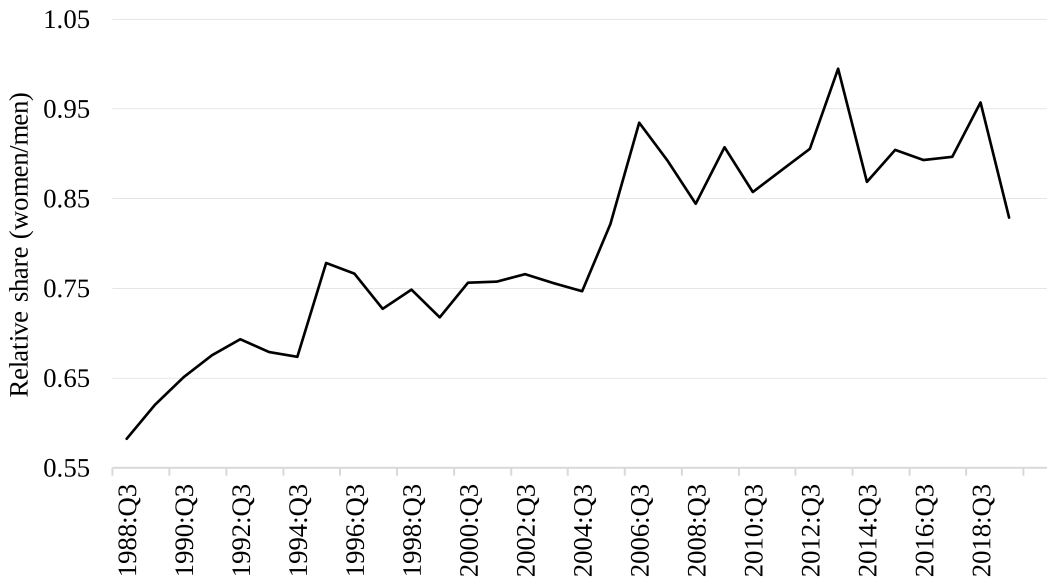
Table 1.3 Composition of the female labor market in Mexico

	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
Highschool	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).

In Figure 1.2, we can observe 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, i.e., there is 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, 0.83 women working for

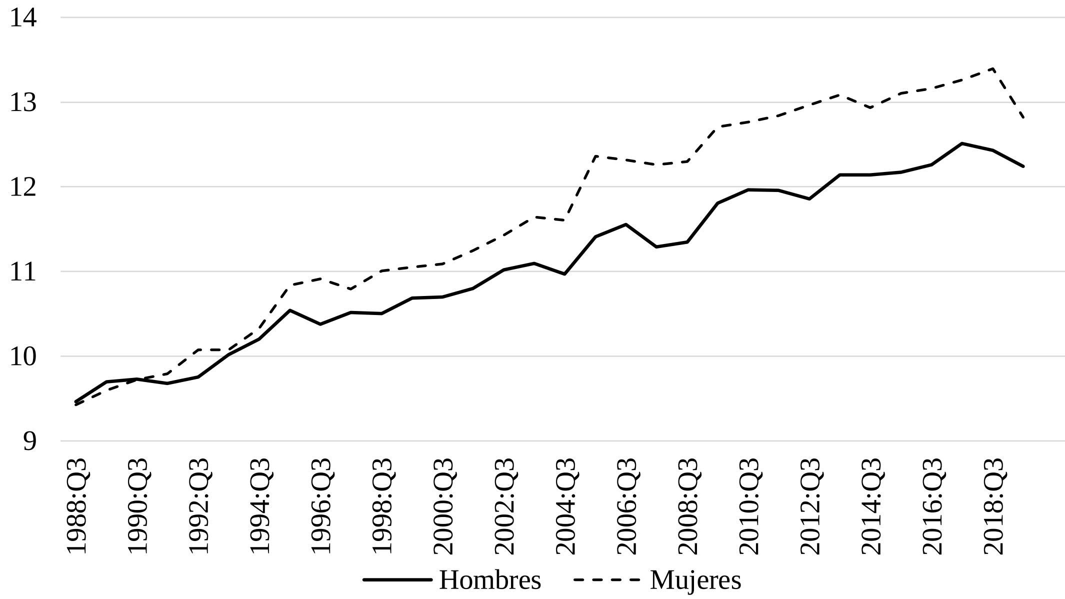
Figure 1.2 Ratio of women's to men's labor force participation rate, 1988:Q3-2019:Q3



Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU(1988-2000), ENE(2001-2004), ENOE(2005-2019).
Notes: Rates are reported for the third quarter of each year for individuals working in the formal sector and receiving positive pay in the urban area. 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.

every man in the labor market; in this case, our estimates suggest that the employment gap was reduced by only 25% for more than thirty years of history.

Figure 1.3 Average years of schooling by gender, 1988:Q3-2019:Q3



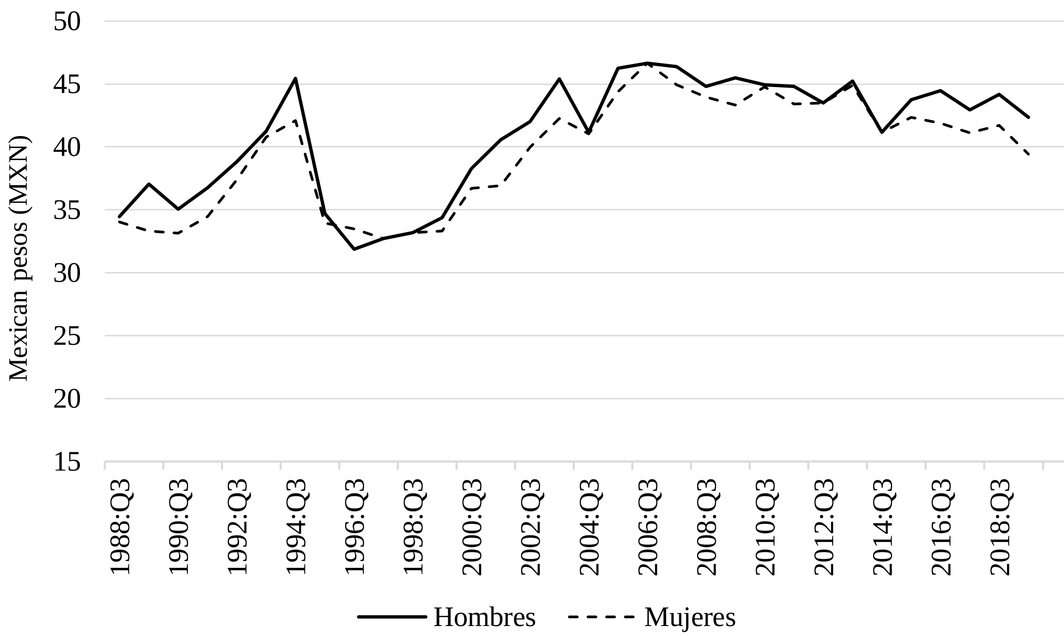
Source: Own calculations with homologated databases from employment surveys in Mexico: ENEU(1988-2000), ENE(2001-2004), ENOE(2005-2019).
Notes: Rates are reported for the third quarter of each year for individuals working in the formal sector and receiving positive pay in the urban area. The sample includes 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.

One of the peaks in Figure 1.2 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 15% compared to the previous period. This result can be derived from the "added worker effect," which has been studied by several authors in labor economics (Cuellar, Moreno, and Luna, 2021; Gomez and Mosino, 2019; Sokufias and Parker, 2006; Humphries, 1988), who propose the female labor market as an escape valve for male employment, this 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, Figure 1.2 shows a constant trend on average in the relative rate of labor participation, despite this unfavorable result.

Education, being a pillar in constructing an individual's human capital, is recognized as a fundamental factor in determining salaries in the market (Becker, 1965; Ben-Porath, 1967; Mincer, 1975). In Mexico, the average woman has completed high school in the formal labor market, while the average man has incomplete high school. A relevant fact in Figure 1.3 is that in 2008, women already reported the same average years of schooling compared to the average reported by men in the last observation of the sample (2019:Q3).

These data series on average years of schooling 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 in the formal labor market in urban areas (comparable metropolitan areas in our sample) in Mexico.

Figure 1.4. 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 positive pay 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.

Finally, Figure 1.4 shows the evolution of median real wages in Mexico. In general, it can be observed that 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 0-4 pesos per hour, with men showing higher stability than women.

Concerning the above analysis, three things 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 in terms of absolute size in the labor market. 3) Real wages in Mexico have been stagnant for the last thirty years. This last point is serious since, 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 proceeds to present the results.

1.4 Methodology and empirical strategy

1.4.1 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 proposed by Mincer (1975). Nevertheless, the estimation is done 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 the estimation of the returns to average schooling and the estimation of expected wages by integrating the previous estimation as an omitted variable.

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

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

<u>Stage 1</u>

$$s_{it}^{j*} = \beta_0 X_{it}^{j} + \beta_{1t}^{women} child_{it}^{women} + \beta_{2t}^{j} \mathbb{D}hh_{it}^{j} + \mathbb{D}state_{it}{}^{j} + u_{it}^{j} \tag{1}$$

Where:

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

$$s_{it}^{j} = 1 \;\; if \;\; s^{*} < 0 \; (the\ individual\ does\ not\ work)$$

<u>Stage 2</u>

$$\ln(w_{it}{}^{j}) = \alpha_{it}{}^{j} + \beta_{1t}{}^{j} sch_{it}{}^{j} + \sum_{n=1}^{4} \beta_{(n+1)t}{}^{j} (age)_{it}^{jn} + \mathbb{D}state_{it}{}^{j} + \delta_{1}{}^{j} \lambda_{it}{}^{j} + \varepsilon_{it}{}^{j} \qquad (2)$$

$$\forall\, j \in (men, women); t \in (1988{:}\,Q1, 2019{:}\,Q4)$$

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 equation (1), we control for observed variables, X_{it}^{j} (dummy variables of the individual's marital status, average years of schooling of the individual, potential experience), but we also add two instrumental variables for women, $child_{it}^{women}$ and $\mathbb{D}hh_{it}^{j}$ (number of children and dummy variable if she is head of household) and for men only if he is head of household, $\mathbb{D}hh_{it}^{j}$, these instrumental variables are directly related to the probability that the individual is working but weakly correlated with wages, which allows us to capture the self-selection bias in the sample.

Equation (1) is implicitly related to the potential output gap estimates since it endogenously estimates the composition and structure of the labor market in terms of 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, equation (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 are the individual's years of schooling i (sch_{it}^{j}), the individual's age i (age_{it}^{j}), this being a way of approximating potential experience[4] . As control variables, we add fixed effects per state, which are represented by dichotomous variables[5] ($\mathbb{D}state_{it}^{j}$). Regarding the unobserved, (λ_{it}^{j}) is the inverse Mills' ratio for individual i which captures

[4] This potential experience approach is proposed by Murphy and Welch (1990) and used by Card (2001).
[5] The dummie or dichotomous variables take values of 1 and 0, depending on the case study.

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 (t) are only indicative, i.e., j they indicate the gender and t the period in which the equation is estimated.

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

1.4.2 Gender wage gap decomposition and extent of selection bias

To estimate gender wage gaps, we propose an extension to the methodology of Blinder (1973) and Oaxaca (1973), 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, which are 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 be reflecting omitted variables or idiosyncratic errors since 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 the expected wages of both groups. 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 and Rubinstein, 2008; Beblo et al., 2003; Dolton and Makepeace, 1986). This effect is incorporated as a result of unobservable factors, but unlike "potential discrimination," selection bias is able to potentially capture unobservable effects associated with the endogenous labor participation decision, such as household structure and reservation wages. Given the relevance of this effect, we devote an exclusive section in the results, in which we will elaborate on this issue.

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

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

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

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

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 since 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 the compensation they receive is at least their reservation wage.

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

$$E[\Delta w] = E\left[w^M | X_i^M, S^M = 1\right] - E\left[w^W | X_i^W, S^W = 1\right] \tag{6}$$

$$= \underbrace{E[X^M - X^W | S^M = 1, S^W = 1]\hat{\beta}^M}_{\text{Endowment effect}} + \underbrace{E[X^W | S^W = 1]\left(\hat{\beta}^M - \hat{\beta}^W\right)}_{\text{Remuneration effect}} + \underbrace{E[X^M - X^W | S^M = 1, S^W = 1]\left(\hat{\beta}^M - \hat{\beta}^W\right)}_{\text{Interaction effect}}$$

$$+ \underbrace{E[\lambda^M - \lambda^W]\hat{\delta}^M + E[\lambda^W]\left(\hat{\delta}^M - \hat{\delta}^W\right) + E[\lambda^M - \lambda^W]\left(\hat{\delta}^M - \hat{\delta}^W\right)}_{\text{Self-selection bias effect}} + \underbrace{\left(\hat{\alpha}^M - \hat{\alpha}^W\right)}_{\text{Residual effect}}$$

Equation (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 effect of the difference in the constant ($\alpha's$), which various authors attribute to "discrimination" between groups (Blinder, 1973; Oaxaca, 1973; Arceo and 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.

1.5 Estimation and results

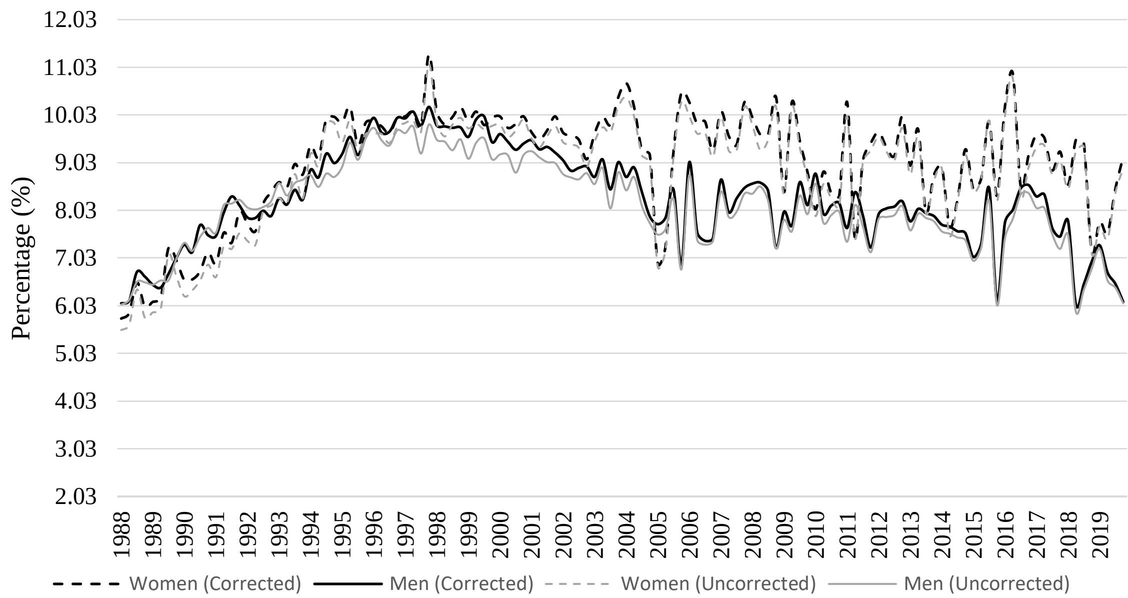
The returns to schooling are estimated using a two-stage "Mincerian" model (Mincer, 1974), representing individuals' productivity through market wages. The first stage is carried out to correct for self-selection bias in the sample (Heckman, 1977), and in the second stage, the calculation estimation of returns to schooling is performed. 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 and 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, as 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.

1.5.1 The historical evolution of returns to schooling in Mexico

In this section, the returns to schooling are calculated for both genders (Figure 1.5). We used a two-stage model (Heckman, 1977), which corrects for selection bias in the sample in the first stage, and as a second stage, the returns to schooling are calculated, which captures $\beta 1$ (equation 2). We find evidence of positive selection bias for women and negative selection bias for men in both groups being 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.

Figure 1.5 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 time series of returns show fluctuations over time, ranging from 5.7-11.3% for women and 6.08-10.2% for men[6]. The gap between men and women is maintained until the 2000s, and from 2001 onwards this difference is reversed, the returns to schooling show increases for women and decreases for men (there is an inverted gap for this period). This phenomenon could be associated with the heterogeneity of opportunity costs determined by the labor market for both groups, since between 2001-2005, the international economic environment underwent substantial changes (China's entry into the WTO), which in the case of Mexico had the effect of recomposing formal and informal employment, i.e., decreases were observed in this same period (Alcaraz and García, 2006; Alcaraz et al.,

[6] See Appendix B presents the returns to schooling micro-estimations time series.

2008). Figure 1.5 also compares returns to schooling corrected for selection bias and uncorrected returns to schooling. If we do not consider selection bias, the returns are underestimated for both males and females. Given that these differences persist throughout the period analyzed, this would imply that the differences in average wages are driven by the heterogeneity between more and less educated women than men on equal terms.

Figure 1.6 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 an increasing behavior from 1988:Q1-2000:Q4, while the opposite is observed from 2001:Q4.

The trend of schooling returns is decreasing, while the trend of average schooling increases for both groups (Figure 1.6) is a finding that coincides with the result found by Patrinos (2016), who estimated and observed that average schooling returns are decreasing for Latin American countries, including Mexico. Specifically for Mexico, Caamal (2017) also coincides with the finding of decreasing returns to schooling by quantiles, which supports our results since, in his analysis, he uses the ENEU and ENOE for a period similar to this study (1988-2013).

1.5.2 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 point in time and compare it to another point in time (Arceo and Campos, 2014; Brown, Pagan, and Rodriguez, 1999).

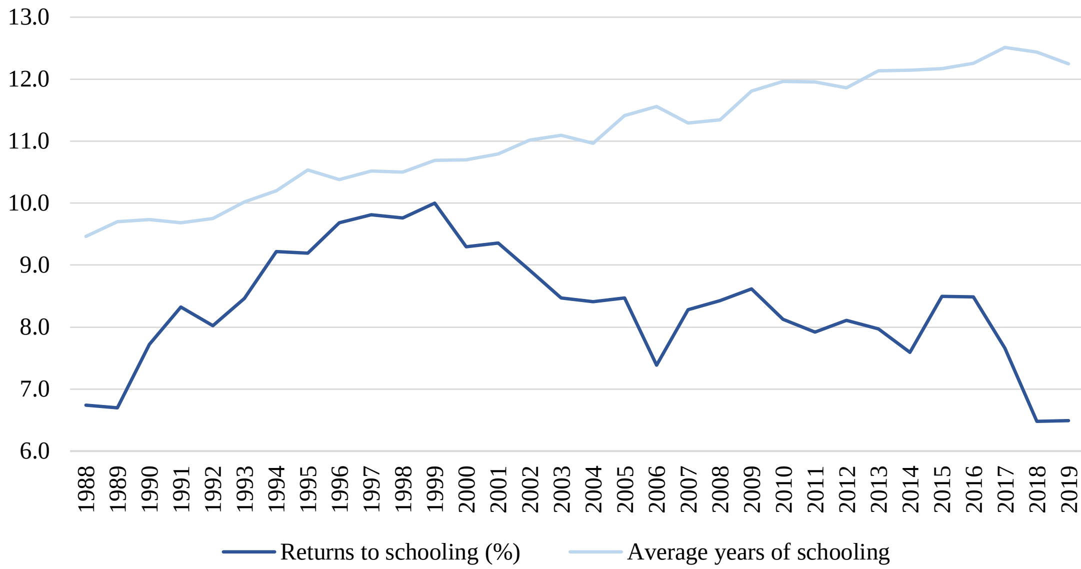
The estimates below capture the trend of the formal labor market gender wage gaps calculated for the period 1988:Q1 to 2019:Q4 (Figure 1.7) regarding the methodology and harmonization of the variables based on the labor market microfoundations for Mexico[7].

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

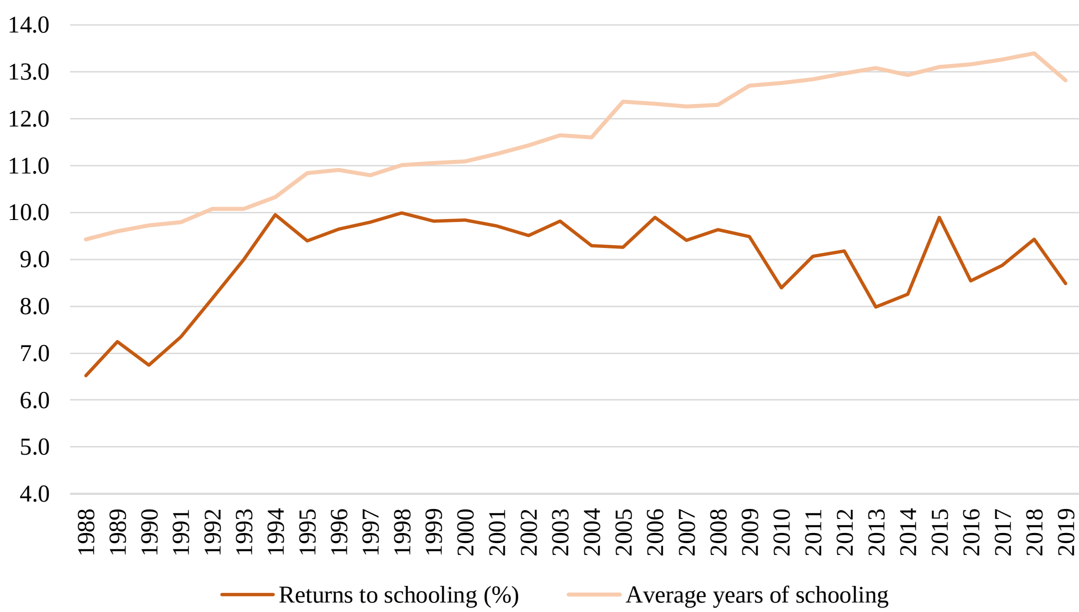
[7] See Appendix C presents the gender wage gap decomposition micro-estimations time series.

Figure 1.6 Returns to schooling and Average years of schooling, 1988:Q1-2019:Q4

Men



Women



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

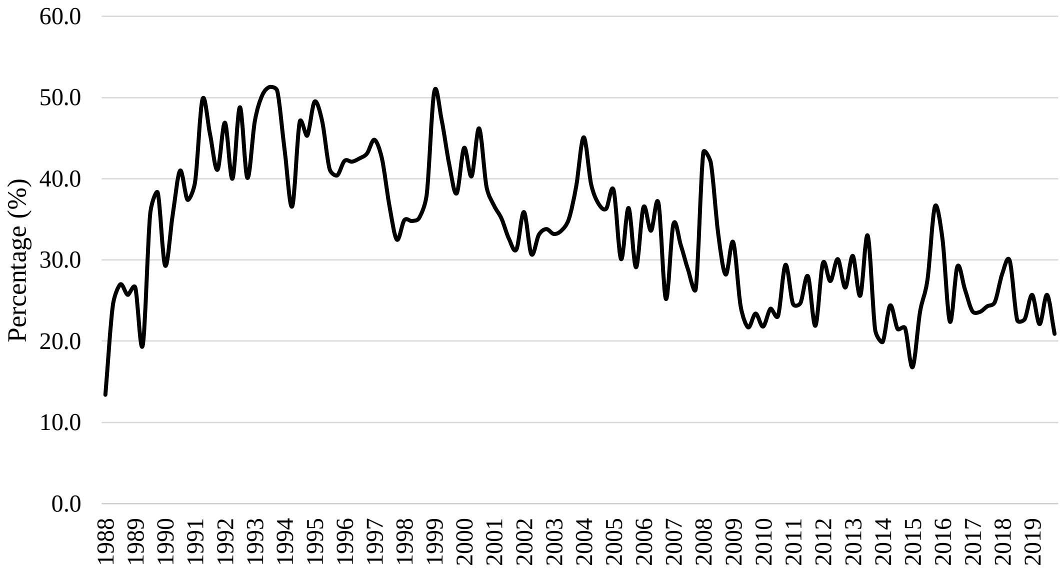
Notes: For returns, each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. Informal employment, persons working without pay, and rural areas are excluded. The sample includes only the following metropolitan areas: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, 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)*

1.5.3 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. The results are presented in two subsections, 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.

Figure 1.7 Gender wage gap (self-selection biased), 1988:Q1-2019:Q4

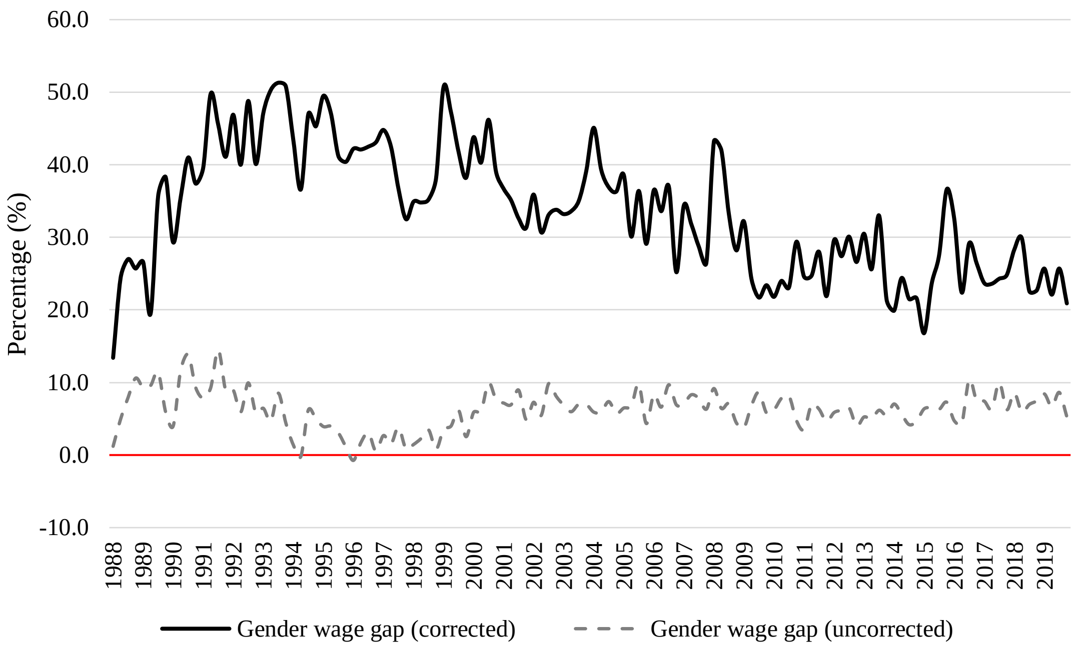


Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU(1988-2000), ENE(2001-2004), ENOE(2005-2019).
Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample 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.*

a) *Effects by observable variables*

Figure 1.9 shows the decomposition of the gender wage gap in terms of its observable factors. Before moving on, we should point out that these effects are not purely net, i.e., their calculation includes the selection bias effect and the residual effect, as we can see 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%.

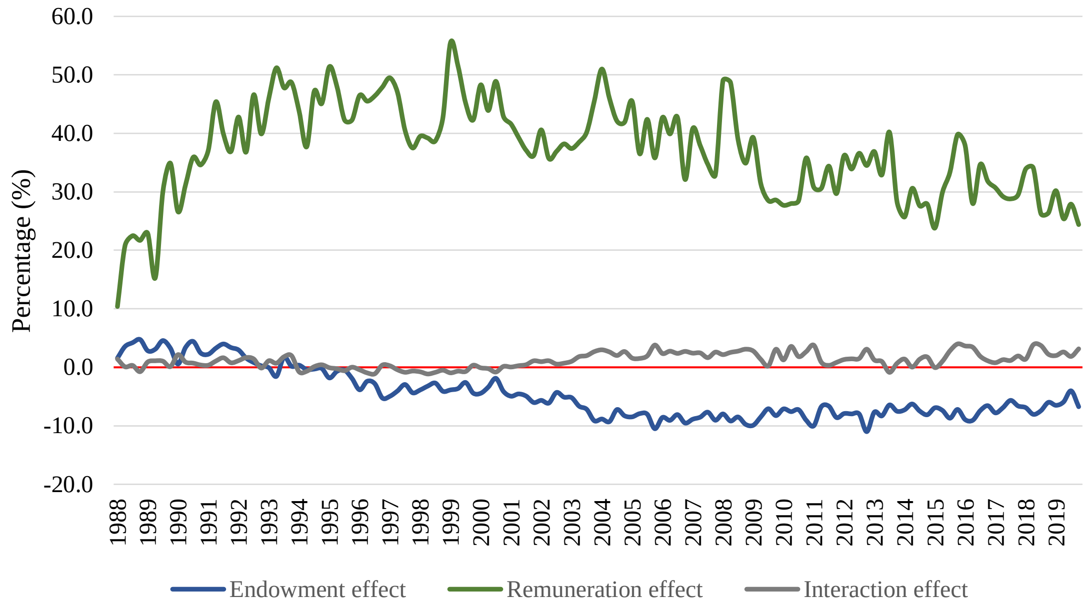
Figure 1.8 Gender wage gap: the self-selection bias, 1988:Q1-2019:Q4



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.*

According to the last result, two things 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, this being a methodological limitation. 2) The remuneration effect captures the residual effect. These two unobservable factors are detailed in the following section.

Figure 1.9 Gender wage gap decomposition, 1988:Q1-2019:Q4

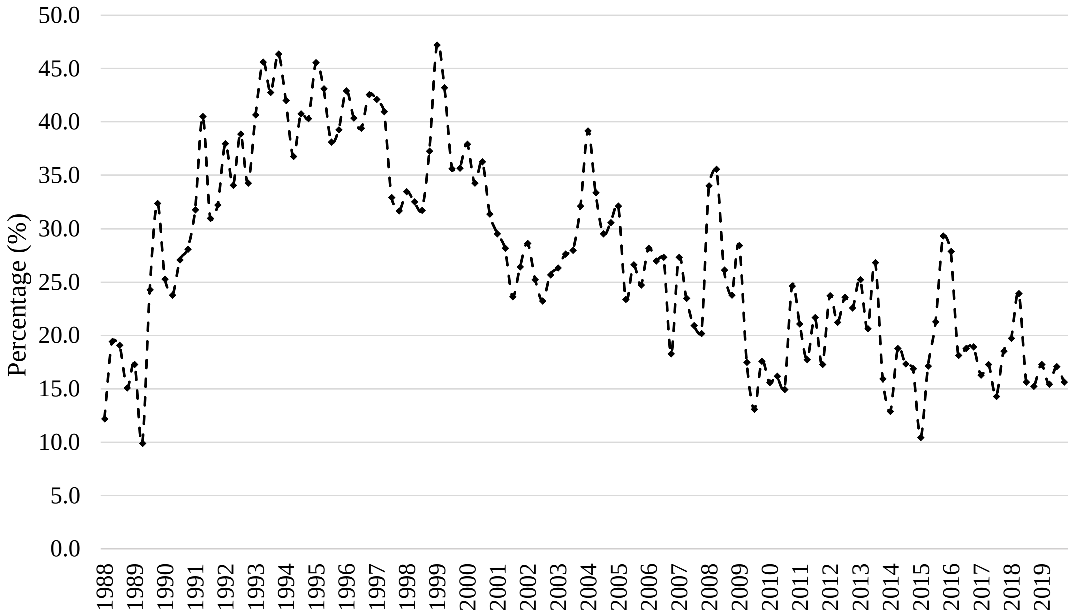


Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU(1988-2000), ENE(2001-2004), ENOE(2005-2019).
Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample 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.*

b) The effects of latent variables (non-observable)

This last subsection 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. Figure 1.10 shows the self-selection bias effect of the gender wage gap decomposition. The trend of this effect fluctuates around 27.4% throughout the period analyzed and is positive. Intuitively, the fact that the self-selection bias is positive can be attributed to the decrease in the labor participation of women relative to men in proportion and characteristics that determine the productivity of individuals in the market (education, work experience), as a consequence, relative wages decrease, and the gender wage gap widens (Mulligan and Rubinstein, 2008; Caamal, 2013).

Figure 1.10 Self-selection bias contribution on the gender wage gap, 1988:Q1-2019:Q4

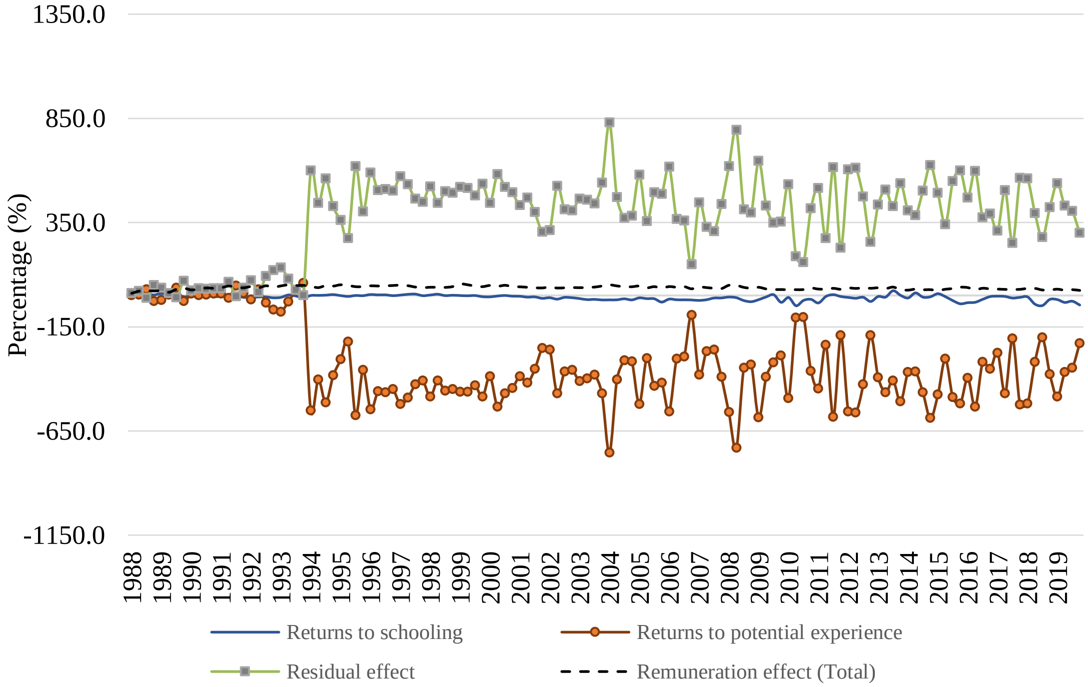


Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU(1988-2000), ENE(2001-2004), ENOE(2005-2019).
Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample 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.*

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, and for this reason, we believe it is pertinent to show the behavior and contribution of this effect over time.

Figure 1.11 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. It can be seen that 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 would give us the residual effect (potential discrimination).

Figure 1.11 Decomposition of remuneration effect, 1988:Q1-2019:Q4

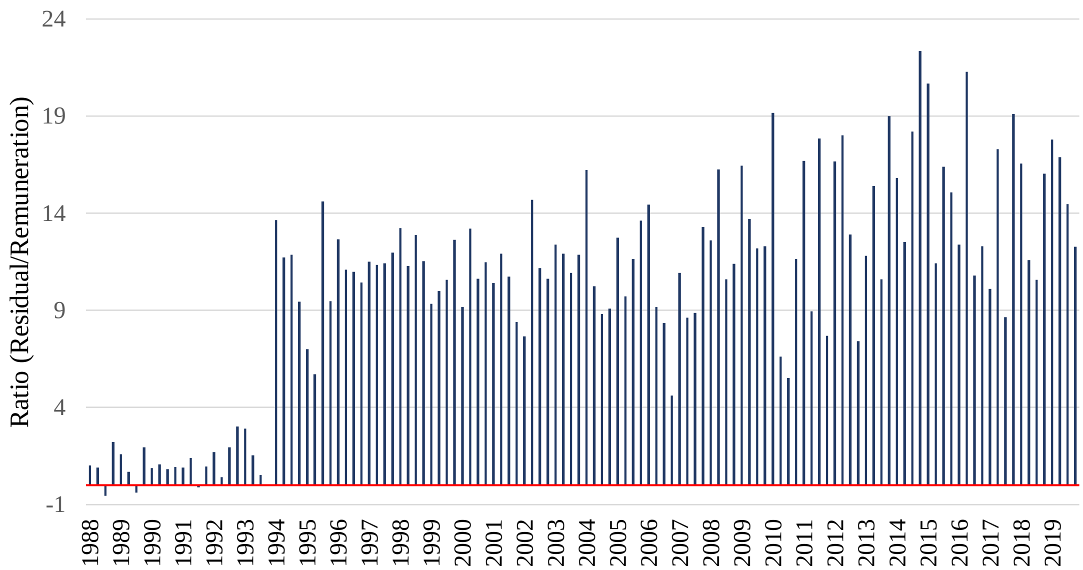


Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU(1988-2000), ENE(2001-2004), ENOE(2005-2019).
Notes: Each micro-founded estimate is reported from 1988:Q1 to 2019:Q4. The sample excludes informal employment, persons working without pay, and rural areas. The sample 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.*

Figure 1.12 presents more clearly 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, as this effect may be capturing omitted variables, 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, so it is worth noting that the unobservable effect that continues to dominate in magnitude is the "self-selection bias."

Figure 1.12 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.*

1.6 Concluding remarks

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. The complex links between inflation, economic growth, and welfare have been known for decades. However, it is still 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 the construction of the databases, variables, and microeconometric estimators provides a historical-comparative context for the gender gap, which is the main contribution of our analysis.

For our work, we used as a basis the model proposed by Mincer (1974) to estimate the returns to schooling, integrating the correction based on the seminal work of Heckman (1979) and used it in multiple other 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 us to identify the observable and unobservable effects of gender wage differentials by integrating micro-founded time series for more than three decades. Thus, we use micro-cliometrics: 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 (decreasing by 30% for men and 14% for women), even though the average years of schooling have increased. In addition, women have been more valued in relative terms by the formal labor market than men since 2001. On the other hand, the gender wage gap has prevailed positively and significantly (around 33% on average) for more than thirty 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 our 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 cost of unemployment 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 where the proposed line of research and the results found in this research will be of great relevance for central banks. In particular, in the last two decades, the reduction of 52% in the gender gap could represent an increase in the relative labor participation of women.

Consequently, a potential increase in the productivity and welfare of society once we consider the returns to schooling and other market factors.

Finally, some of the future lines of work derived from this micro-cliometrics approach would allow us to study the gender differences in formal and informal employment. Also, to make an extension to integrate the cycles between unemployment, formal employment, and informal employment, seeking to deepen the study of the heterogeneity of both genders and sectors of the economy, as some authors have done for Mexico (Alcaraz and García, 2006; Alcaraz et al., 2011; Levy, 2018; Escobedo and Moreno, 2020; Maloney, 2004; Moreno and 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 the design of public policy that consider the complex relationships of each agent with the institutions where they interact and make decisions.

CHAPTER II. Employment, gender gap, and the Mexican industry: the effect of covid-19 on the dynamic structure and recovery in the labor market[8]

2.1 Introduction

The COVID-19 crisis represents, at the moment this chapter is written, the most critical challenge our society has faced in economics, financial, political, and public health over the XXI century.

In March 2020, the World Health Organization (WTO) declared the SARS-CoV-2 virus and the derived COVID-19 disease crisis a pandemic. As a result, almost two-thirds of the countries around the world paralyzed their economic activity, affecting all industrial sectors and employment worldwide. The effects of this period, known as the "Big Confinement," introduced sudden stops in most economic activities and changed dynamics with both temporal and permanent effects on the organization of the world economy (IMF, 2020). As an expected result, these effects permeated the labor market and potentially accentuated differences in job opportunities for women and men according to their skills, education, and experience across different industrial sectors (Siddiqui, 2020).

This complex scenario was particularly unfavorable for Mexico as the services sector, one of the country's primary sources of income, including entertainment and tourism, was the first to respond to the negative shock (Esquivel, 2020). Furthermore, the evidence from the different economic sectors of the country shows a sizeable structural impact on production and employment levels (Coparmex Nuevo Leon, 2020; ENOE, 2020). As a result, this economic impact translated into around half a million employment losses in the country's formal sector during the first half of the pandemic (INEGI, 2020).

Henceforth, identifying the relationships between the industrial structure and the different labor market segments is critical for understanding the employment dynamics, recovery,

[8] Accepted chapter: Moreno, J., Cuellar, C. & Ramos, M. (2023). Employment, gender gap, and the Mexican industry: the effect of covid-19 on the dynamic structure and recovery in the labor market. In *Rebuilding after the Great Confinement: Human, Economic and Technological Levers*. Palgrave Macmillan, Cham. [Forthcoming]

and connection with contingencies due to the COVID-19 economic crisis. These long-term relationships and their short-term components are valuable tools for evaluating the potential effectiveness of public policy to alleviate the impact on the labor market in the short and long run.

This chapter analyzes the dynamics, persistence, and changes in the Mexican labor market resulting from the COVID-19 economic shock, focusing on the impact on the gender gap. The labor market is divided into six segments according to two main dimensions: aggregate economy sectors (primary, secondary, and tertiary) and gender (men and women). This approach allows us to identify differentiating effects and heterogeneous changes across the labor market structure. The differentiated analysis between groups, mainly gender, will enable us to recover the heterogeneous structures in the market and thus compare long-term trends and dynamics in the Mexican labor market segments (Cuellar, 2019; Moreno & Cuellar, 2021).

With this objective, this research builds micro-founded employment time series which recover consistent and homologous Mexican labor market data over time. The aggregate data is organized quarterly from 1993:Q1 to 2021:Q4, focusing on urban areas and three industrial sectors: primary, secondary, and tertiary[9]. Following a theoretical neoclassical approach of production, factor demand, and economic growth (Akkemik 2007; Moreno & Cuellar, 2021), the time series of employment in Mexico are segmented by industrial sectors and gender. Afterward, the empirical research strategy defines and estimates a VAR model that links each employment segment with the sectorial economic activity defined by the GDP to identify the depth and persistence of the first COVID-19 pandemic shock (*I-shock* COVID-19). Then, to perform the impact analysis, impulse-response functions are estimated by introducing the first shock observed in the economic activity of the Mexican GDP in the first quarter of 2020, sizeable to the actual first impact of COVID-19, and forecast the trends of employment by segments. As a result of these estimates, we forecast the counterfactual trends to compare what would have happened if the *I-shock* COVID-19 shock had not existed. Finally, this methodology allows a

[9] The urban areas historically represent more than 70 percent of the total employment in Mexico.

comparative analysis with observed employment dynamics to identify structural changes and potential recovery in each employment segment with these forecasted trends.
This study contributes to the business and economic literature in four dimensions. First, the methodology uses *consistent* time series constructed from micro-data in all employment surveys for Mexico during the analyzed period. Second, it is the first study that analyzes the particular dynamics of the *industrial sector employment* in Mexico, identifying potential long-run structural changes in the labor market. Third, it estimates dynamic employment models by gender and industry segments and identifies heterogeneous impacts on the employment gender gap resulting from the *I-shock* COVID-19. Finally, this study estimates the long-run trends for recovery periods for each sectorial labor market segment. The research concludes by comparing the actual recovery to the long-trend estimates, which will measure the potential structural change in industrial employment and the employment gender gap.

Identifying changes in the long-run trends and the short-run observed components of employment is a valuable tool for analyzing public policies' potential impact on alleviating economic shocks during the pandemic. For instance, the evidence provided in this research suggests that the implementation of public policies by the Mexican federal government, such as "on-the-job training" scholarships (prior to the COVID-19 crisis) or the prohibition of outsourcing jobs force them to become formal employment (during the COVID-19 crisis), might indeed have a limited or null effect on the long run employment. These limited impacts could be related to the solid structural trends and traduced in limited effect in the short run over the labor structure due to the pandemic incidence.

The chapter is divided into six sections, including this introduction. The second section presents the theoretical framework and literature review, emphasizing previous findings related to the methodology, the regional labor market, and the COVID-19 crisis. The third section shows the data and methodology proposed to study regional employment dynamics divided by industrial sectors and gender. The fourth and fifth sections present the results and the discussion of the study. Finally, the sixth section presents the conclusions and implications of the analysis.

2.2 Theoretical framework

2.2.1 The labor market, productivity, and the economy: the model

This study uses a neoclassical theoretical framework (Arrow et al., 1961) applied to the labor market (Akkemik, 2007; Moreno & Cuellar, 2022). This framework assumes perfectly competitive markets, where the production function is of CES-type, and there are factors of production, which are capital (K) and labor (L); this function has returns to scale defined by the parameters s and ρ. In Equation 1, "rho" is a positive parameter that measures the elasticity of substitution of capital and labor. From the optimality conditions, it can be observed that the marginal productivity of both factors equals their market price, r, and w (Equations 2, 3, and 4). Equation 5 takes logarithms from the labor's first-order condition and rearranges terms.

$$Q = f(K,L) = \theta[\beta L^{-\rho} + (1-\beta)K^{-\rho}]^{\frac{s}{\rho}} \quad (1)$$

$$f'(K,L) = f_k = r \quad (2)$$

$$f'(K,L) = f_L = w \quad (3)$$

$$\frac{\partial Q}{\partial L} = s\theta^{-\rho s}(1-\beta)Q^{1+\rho/s}L^{-1-\rho} = w \quad (4)$$

$$\ln L = \alpha_0 + \alpha_1 \ln Q + \alpha_2 \ln w \quad (5)$$

$$\alpha_0 = -\frac{1}{1+\rho}\ln(s(1-\beta)) - \frac{\rho s}{1+\rho}\ln\theta, \quad \alpha_1 = -\frac{1+(\rho/s)}{1+\rho}, \quad \alpha_2 = -\frac{1}{1+\rho}$$

The α_0, α_1 and α_2 parameters of equation (3) are combinations of the structural parameters of production and show the equilibrium effect on the labor market derived from economic activity (expected positive) and wages (expected negative).

This neoclassical theoretical framework permits the recovery of the causal structural effects caused by the exogenous shocks derived from the COVID-19 pandemic on the different segments of the labor market in Mexico. The following subsection presents the data and methodology used to analyze the expected effects on the labor market structure.

2.2.2 *Industrial employment, gender gap, and the COVID-crisis: the evidence*

The International Labour Organization (ILO) states that the COVID pandemic affected labor markets in all regions, but the recovery patterns are very different. Europe and North America presented a faster recovery, with the most pessimistic outlook for Southeast Asia, Latin America, and the Caribbean. The differences between countries with the most robust labor market recovery are observed in high-income countries, while low-middle-income economies show a slow recovery (ILO, 2020).

In terms of the industrial heterogeneous effects, according to Gasca (2021) the pandemic in Mexico caused government institutions to decree a production stoppage in March 2020. Consequently, the policy caused a slowdown in GDP, presenting differences in the decline according to the productive sectors or regional patterns. In particular, the results in Gasca (2021) show a more significant decrease in states with high concentration and entities dedicated to the automotive and electronics industry (the central-western region and the north of the country). Jimenez-Bandala et al. (2020) review the panorama of the Mexican labor market and conclude that the regional recovery is asymmetric and uneven, reproducing the inequalities existing prior to the pandemic. The northern and western states presented a rapid readjustment in employment, but the center and south fell to a greater extent and presented a slow recovery.

Regarding the gender employment gap, the evidence in Latin America and Mexico is strong. Garcia et al. (2018) report a gender wage gap due to men, on average, dedicating more hours to work per week. The gender wage gaps by occupation are represented as follows: 60% in industrial and 61% in services.

Mancini (2016) concludes that women were not inserted in a large proportion in the manufacturing sector and "enter practically directly into the service sector or commerce." He also points out that women's entry into the labor market occurs later and with more qualifications than men. In a longitudinal analysis carried out for three generations of women, he observes that occupational mobility by the branch of activity is not very significant. He also points out the delay at the beginning of the labor trajectory and the increase in educational levels.

On the other hand, Fernandez and Lugo (2017) found that in 32 Mexican urban areas between 2005 and 2016, female employment increased compared to male. In particular, the female population was mainly in part-time shifts. They also identified that the weighted average of the participation rate of qualified women was equivalent in 2005 to 82 percent of that of men and rose to 85 percent in 2016. At the same time, the weighted average of the participation rate of unskilled women went from 80 percent of men in 2005 to 55 percent in 2016, and the labor gender gap has reduced for people with higher education. Despite this, there are still significant differences in income for women with low levels of education.

Cerquera-Losada et al. (2020) analyzed the gender wage gap in Colombia in 2017. When analyzing the productive characteristics, they conclude that women with even better characteristics (education, experience, among other variables) obtain lower remuneration than men. Furthermore, they indicate that, even though women have increased their participation with higher levels of education, the remuneration obtained still does not correspond.

In the Argentine labor market, Paz (2019) reveals that the context variable with the most significant weight in the salary gap is the participation of women in the non-formal segment, mainly among married women. Thus, married men outperform women precisely because they spend more time on paid work.

Felix-Verduzco and Inzunza-Mejia (2019) confirm the importance of professional education to increase labor participation but also verify the persistence of gender roles. Their analysis focused on women between 25 and 54 years old, and their crucial result is that the probability of labor participation is always higher in single women than in married women. For example, for the technical and professional levels of study, the probabilities of labor participation between married and single tend to converge when the potential labor income is high enough.

Pelaez and Rodriguez (2020) point out that men start their first job younger than women, particularly those with higher education. The fact that younger people remain in the educational system until reaching a higher educational level not only delays the start of working life but also tends to reduce the gender gap in the calendar of entry to the first job. This fact increases the probability of accessing the occupational stratum of higher status and hierarchy: directors, managers, and professionals (44.1% for men and 47.8% for women).

Bracamontes et al. (2020) analyzed the characteristics of the employed population in 2005 and 2017, identified the 11 different branches of the economy, and classified Mexico into regions of high, medium, and low exposure to trade openness. Between 2005 and 2017, the wage gap was reduced in the country, and each of the three regions favored women. However, higher wages are observed in the area most exposed to commercial opening, and higher wage differences favor men. The sectoral analysis shows that the labor participation of both genders in commerce, manufacturing industry, and services has increased. Within the regions, gender differences persist in the regions of high exposure. It was found that most women continued to be located in commerce and most men in manufacturing; in those with low and medium exposure, most women and men were placed in commerce.

Ripani and Azuara (2021) point out that the pandemic labor crisis in Latin America affected the most vulnerable population to a greater extent, including the least educated young people and those in the informal sector. Workers with low education have lost jobs between 3 and 4 times more than those with high education, particularly women, accentuating regional inequality. However, female employment remained at lower pre-pandemic levels.

Gomez (2021) points out that in the Mexican labor market, the impact of the pandemic has been more significant on women. By 2020, the probability of a woman's employment decreased by four percentage points compared to the reduction experienced by men. The sectors with the most significant loss of employment were the services sector, specifically in the retail and wholesale business, food and beverage preparation, domestic work, leisure and cultural services, and light manufacturing.

Salce (2021) investigates the evolution of salary discrimination in Chile by gender by analyzing the information provided by the CASEN survey, from 1990 to 2017, with intervals of two or three years between each survey. The results reveal that when comparing a woman with a man with the same characteristics and equal qualifications, the woman will receive, on average, a lower salary than the man. In Chile, the wage gap has always favored men, standing at 9.8% in 2017. In addition, it has been observed that the labor market demands more educated women than men, yet the salary is lower than men. For example, in 2017, employed men had 8.9% fewer years of schooling than employed women.

On the other hand, in the case of the unemployed, it is observed that unemployed men had 4.3% more years of education than women in a similar situation for the same year. Another of the results indicates that potential discrimination is present mainly in the poorest and wealthiest extremes when separated by income quantiles into 10% of the population with minors and 10% with higher incomes. In addition, it shows that the most relevant variable that makes up wage discrimination is work experience, while years of education help reduce it.

So far, the literature analyzes the employment dynamics by industry and gender segments, mainly along and after the pandemic crisis. Hence, one of the main contributions of this work is to present a dynamic analysis of industry heterogeneity in the labor market, differentiating employment by gender. This approach permits the analysis of COVID-19 impact on employment in Mexico and estimates the potential recovery of employment in the defined market segments.

2.3 Empirical strategy

2.3.1 Data

This research makes use of three historical employment surveys in Mexico: the National Urban Employment Survey (ENEU), the National Employment Survey (ENE), and the National Occupation and Employment Survey (ENOE). This quarterly microdata is public and published by Instituto Nacional de Estadistica Geografia e Informatica (INEGI). The available periods for the ENEU are 1988 to 2004, for ENE from 1998 to 2004, and ENOE from 2005 to date.

The study constructs quarterly aggregate time series for each labor market segment in Mexico from 1993:Q1 to 2021:Q4. Therefore, the following time series are constructed for each market segment: *primary sector – male, the primary sector – female, secondary sector – male, secondary sector – female, tertiary sector – male, tertiary sector – female*.[10]

Thus, the main objective is to obtain the structural changes due to the COVID-19 pandemic and recover the new labor market structure defined by these segments. In addition, this approach allows us to construct a counterfactual trend (i.e., what would happen if the COVID-19 pandemic never existed) to identify structural changes in each employment segment. Finally, the pre-COVID-19 trend in employment is forecasted as implied by the parameter estimation of long-run trends and compared with the actual values of the employment post-COVID-19 to the analysis to estimate the COVID-19 impact on labor market segments.

We link employment to the Mexican economy's performance to accomplish the main objective. For this purpose, we use each industrial sector's GDP to measure economic activity extracted directly from INEGI's information bank. The real average hourly wages are estimated directly from the Mexican employment surveys.

[10] For further details on the methodological construction of the micro-founded time series, see Moreno and Cuellar (2021); Cuellar and Moreno (2022).

To conclude, the construction of the time series of employment and wages is limited to the employment growth rates for this research. Therefore, the final micro-founded time series sample consists of individuals between 16 and 65 working and receiving a monetary payment greater than zero in homologated Mexican areas[11] for the defined period.

2.3.2 Econometric specification

This chapter follows the labor market's dynamic neoclassical equilibrium approach, considering the relationship between economic activity and employment segments. This model implies long-run equilibrium causality relationships between production, productivity, employment, and wages (Arrow et al., 1961; Akkemik, 2007; and recently for Mexico Moreno & Cuellar, 2021; Cuellar & Moreno, 2022).

The econometric strategy to analyze such long-run relationships is based on a Vectors Auto-Regressive (VAR) model in reduced and unrestricted form. This method permits studying the linear simultaneity between all the relevant variables and finding persistence between the same series in the long run, with the correct specification of the lags. Likewise, since the technique does not impose restrictions on the model, it avoids specification errors (Sims, 1980). This model also allows us to estimate the causal impact of the economy on employment, so this theory will enable us to propose an empirical model with simultaneous interactions between these variables.

The time series vector of interest $y_t = [y_{it} \;\; y_{jt} \;\; y_{kt}]'$ is presented in growth rates, where y_{it} is *i-employment segment* employment, y_{jt} is the GDP sector for the *j-industry sector* and y_{kt} is the real hourly wage *for gender k*. Each vector has its respective autoregressive component ($t{-}p$) and a component associated with the white noise process, ε_t. The reduced VAR model can be represented in terms of its characteristic polynomials defined over the number of "L" lags, $A(L,\phi)$ *and* $B(L,\theta)$ as follows:

$$y_t = A(L,\phi)y_{t-p} + B(L,\theta)\varepsilon_t \tag{4}$$

$$A'(L,\phi)y_t = B(L,\theta)\varepsilon_t \tag{5}$$

[11] Metropolitan areas included: Mexico City, Guadalajara, Monterrey, Puebla, Leon, Torreon, San Luis Potosi, Merida, Chihuahua, Tampico, Orizaba, Veracruz, Ciudad Juarez, Tijuana, Matamoros, and Nuevo Laredo.

A unit root test will have to be performed on each vector to test the stationarity of each vector; details will be shown in the results section. Given the time stationarity of the series joint distribution, the system can be represented in terms of the Gaussian white noise process as in Equation 6 using the Yule-Walker characteristic polynomials. The new characteristic polynomial described by $C(L, \phi, \theta)$ is unique for each VAR process defined over the number of lags (L). With this, a maximum likelihood method through the properties of the Gaussian process is used to recover the parameters associated with the original model, $\{\phi, \theta\}$.

$$y_t = \frac{B(L, \theta)}{A'\,(L, \phi)} \varepsilon_t = C(L, \phi, \theta) \varepsilon_t \tag{6}$$

Given that our primary objective is to analyze the impact of the I-shock of the COVID-19 pandemic on employment segments, each segment model's Impulse-Response Function (IRF) is used to capture the response of the model variables to an unanticipated "shock" in the idiosyncratic component of the model (ε_t). The variance decomposition of the orthogonal error term on the random innovations of each endogenous variable belonging to each model permits getting information on the correlations and variances for each exogenous shock.

Once the IRFs are obtained, where the impulse is in economic activity (GDP) and the response is in employment, employment levels are retrieved to compare pre-COVID-19 trends, I-shock COVID-19 trends, and the observed structure of employment.

2.4 Estimation and results

2.4.1 Time series identification and decomposition

The study analyzes and compares employment recovery trends segmented by sector and gender in Mexico. Once the model is estimated, the result is compared with the observed employment structure (the most recent data is 2021:Q4).

The methodology proposes to estimate two series with the actual employment to capture the impact of the first COVID-19 shock to analyze the structure and compare the recovery of jobs by the segment of the industrial sector and gender: i) the *Pre-COVID-19 trend*: forecast the level of employment and are calculated based on the VAR model used in the methodology describing the expected level of employment if the COVID-19 crisis did not happen, ii) *I-shock COVID-19 + Pre-COVID-19* trend time-series forecast employment levels given the first shock due to the crises (GDP) and the respective trend from this impact, and iii) *Actual employment*: theses series show the jobs levels observed for Mexico in each industrial sector segmented by gender.

These analyses allow us to recover the employment sectors' counterfactual gaps segmented by gender: 1) Pre-COVID-19 vs. post-COVID employment long-run trend. 2) Pre-COVID-19 vs. current employment trend. 3) Post-COVID-19 vs. current employment trend.

Trends and gap impact on employment are estimated by introducing a negative shock equivalent to the observed effect of COVID-19 crises on GDP through the IRFs of the VAR model. Moreover, the VAR model will estimate the pre-COVID-19 trend, differentiating what would have been without the pandemic. Finally, the observed employment captures the magnitude of the structural effects, and with this, potential recovery scenarios are projected in the different employment sectors segmented by gender.

2.4.2 Unit root test and selection criterion optimal lags

Before estimating the model, the VAR's validity and stability are tested by performing unit root tests on each series of interest and optimal lags criterion tests. The time series are presented in growth rates, so two-unit root tests were performed: Augmented Dickey-Fuller (ADF) and Phillips-Perron unit root test to test the series' stability in the long term.

Table 2.1 presents the stationarity tests for the GDP, the employment sectors, and the real hourly wage. These time series are segmented by gender. It is observed that all series are stationary in both tests, so these series are consistent with order-one I(1) data.

This study uses an unrestricted VAR model, so a critical point is the order of the variables and the optimal number of lags to be used in the models. For the analysis, the theoretical framework model is used to sort variables in the following order: employment-GDP-real wages.

The reduced VAR model requires a lag criterion of estimation. According to the literature, it will be presented that the model should have one lag, given the size and periodicity of the series (Ivanov & Kilian, 2005)[12]. Table 2.1 shows that three groups (SBIC) suggest it should be zero lag (FPE, AIC, HQIC) propose one lag, and LR proposes five lags.

2.4.3 Employment segment IRF's analysis

Focusing on employment by gender and the industrial sector, the model follows the market-implied behavior after introducing the I-shock COVID-19. This section presents the main contribution of our research, which is to recover and quantify the impact of the I-shock COVID-19 on employment by segment defined on the industrial sector and gender in Mexico.

Firstly, the time series are segmented by industrial sector structure (*primary, secondary* and *tertiary* employment) and gender to understand the labor market dynamics. It allows us to rely on Impulse-Response Functions to estimate the impact, using economic activity (Mexico's GDP) as the impulse variable. The response variables are the different sectors by gender in the labor market. For the VAR model (Annex 1), the response variables are Primary/Secondary/Tertiary men's employment and the same sectors for women; all segments belong to the homologized cities of the standardized sample.

The model introduces as *I-shock COVID-19* the observed change in economic activity (Mexico's GDP) for the first quarter of 2020 (INEGI, 2020), which represented a -2.2 standard deviation (s.d). Although the magnitude of the impulses in the IRFs frequently is introduced in one standard deviation, in the model, we use the first shock to observe its dynamics in the labor market. Figure A.1 (Annex 1) presents the Impulse-Response

[12] This study does not recommend making inferences of individual coefficients due to the high multicollinearity among the variables (Akkemik, 2007). However, the model's statistical properties are reported in the annexes for information (Annex 1).

Functions for the model differentiated by the employment sector and segmented by gender structure.

Figure A.1 shows how the *I-shock-COVID-19* impacts labor employment divided by gender and sector. The model allows us to aggregate the negative impact in period t+1. With this, it is possible to observe that the primary sector labor market is inelastic to shocks in the Mexican economy. One of the reasons may be that the primary sector is highly dependent on external supply and demand, so the labor market has its behavior. On the other hand, Figure A.1 displays the impact of the COVID-19 shock on both jobs in the secondary and tertiary sectors. For Mexico, the manufacturing industry fell by 10.9% in the first four months (INEGI, 2020); in our model, this fall of the first shock represents 1.6% for men and 1.5% for women.

The first COVID-19 shock also significantly impacted the tertiary sector employment due to the high adjustment cost of the sectors. The crisis hits those sectors more intensely with greater technological dynamism, resulting in changes in the country's production structure (CEPAL, 2020).

Also, the COVID-19 *I-shock* relative to gender has different dynamics between sectors. While in the secondary sector, the impact is more profound for women (1.6% vs. 1%), the opposite is true for the tertiary sector, where male employees received a greater shock than women (1.5% vs. 1.3%). The tertiary sector had the most significant impact from the pandemic since the first shock to hit Mexico was tourism (Esquivel, 2020). This sector accounts for a large part of tertiary employment.

These impulse-response functions allow us to recover the trend with the *I-shock* COVID-19 in employment sectors by gender, and then, with the VAR model, the pre-COVID-19 trends are estimated. The following section includes the differences between the employment losses derived from the I-shock and the losses derived from the structural effects triggered by the COVID-19 shock.

Table 2.1 VAR model: tests and selection criteria

Z-statistics for hypothesis testing unit roots

Growth rates	**Augmented Dickey-Fuller (ADF)**		**Phillips-Perron Test (PP)**	
GDP	-7.53	***	-79.46	***
Men				
Employment sector-Primary	-11.15	***	-111.09	***
Employment sector-Secondary	-10.04	***	-105.20	***
Employment sector-Tertiary	-15.11	***	-130.93	***
Wage per hour	-13.64	***	-148.32	***
Women				
Employment sector-Primary	-13.91	***	-128.04	***
Employment sector-Secondary	-10.88	***	-118.00	***
Employment sector-Tertiary	-16.79	***	-128.97	***
Wage per hour	-12.78	***	-134.85	***

*p-value: 0.01***, 0.05**, 0.10*.*

The selection criterion for optimal lags in VAR models

Model: Employment sectors

Lag	**LL**	**LR**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	1501.07		1.6e-24	-29.2562	-29.1624	**-29.0246***
1	1631.52	260.91	**6.1e-25***	**-30.2259***	**-29.2881***	-27.9098
2	1711.94	160.83	6.4e-25	-30.2145	-28.4325	-25.8138
3	1770.33	116.79	1.1e-24	-29.7712	-27.1451	-23.286
4	1833.94	127.22	1.8e-24	-29.4302	-25.96	-20.8605
5	1905.61	**143.33***	3.0e-24	-29.2472	-24.9329	-18.5929

**Selection criterion*
Source: Own estimations with time series constructed and homologized of employment surveys (ENEU-ENE-ENOE). Seasonally adjusted series presented by growth rates.
Notes: Sample 102 observations. LL: log-likelihood, LR: likelihood ratio, FPE: final prediction error, AIC: Akaike's information criterion, HQIC: Hannan and Quinn information criterion, SBIC: Schwarz's Bayesian information criterion.

2.5 Discussion

2.5.1 Impact on employment sectors and gender

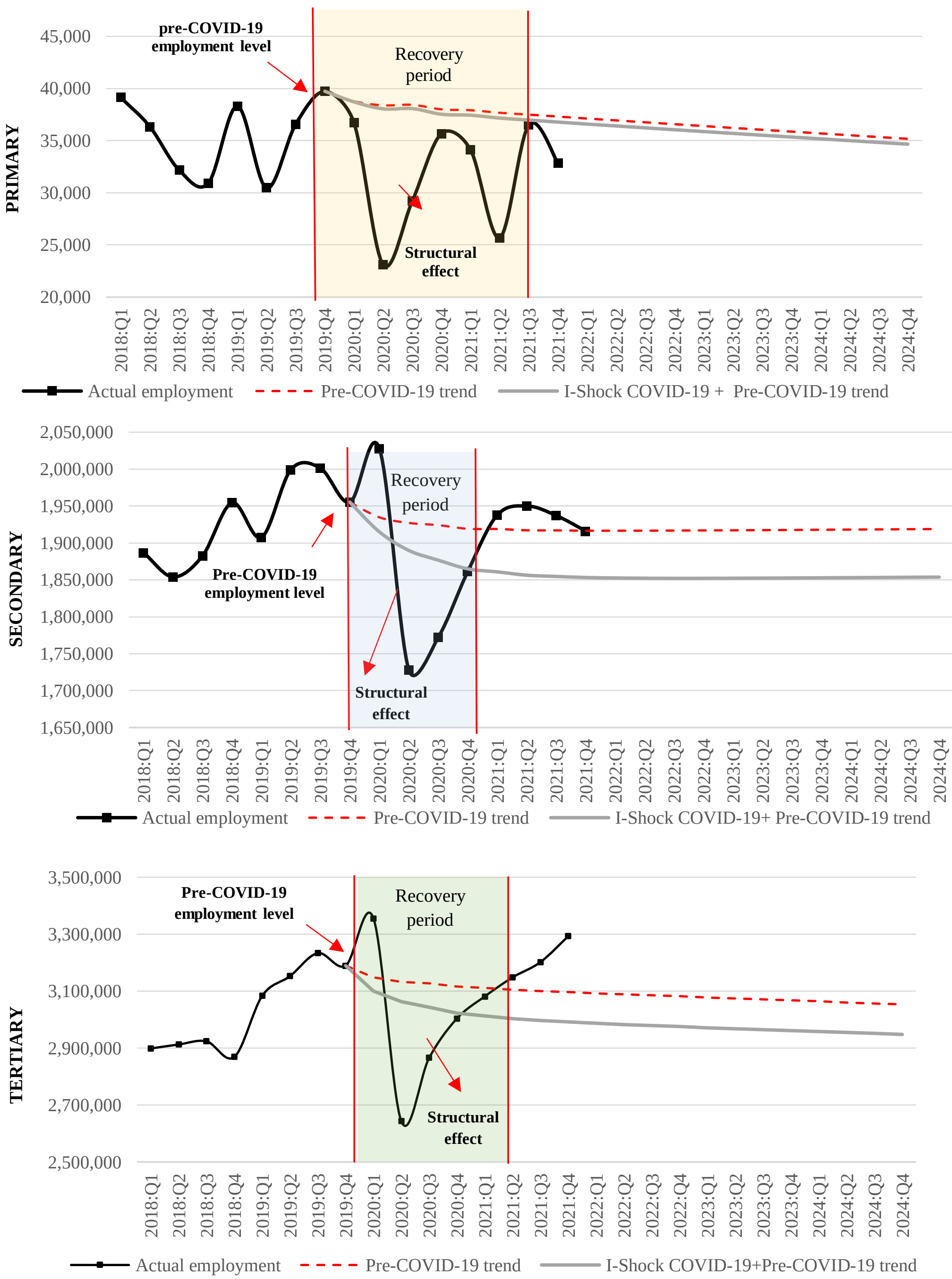
As in previous works, employment in Mexico presents a particular structure and dynamics, depending on the context and issues in which the data are analyzed (Cuellar & Moreno, 2022; Moreno & Cuellar, 2021). First, this study introduces the economic I-shock derived from the COVID-19 pandemic. Then, it explores the impact on long-term employment growth trends among six primary, secondary, and tertiary segments segmented by gender. Once the trends are calculated, a counterfactual trend analysis is performed, i.e., the observed employment is analyzed against the pre-COVID-19 and I-shock-COVID-19 trends, giving a generalized context of what would have happened to employment if the pandemic had not occurred.

Figures 2.1 and 2.2 show the cumulative employment loss segmented by sector for men and women, compared to employment trends (one without the COVID-19 shock and the other including it). Our results are divided into impacts on elasticities, cumulative observed employment loss, and long-run employment growth trends.

The first result highlights the elasticities of employment in each economic sector. It can be observed that tertiary employment is more reactive or elastic to shocks produced by the economy, while primary sector employment is inelastic to these same shocks; this is in aggregate for both genders (see Figure A.2: Model). This finding is in line with other authors, who found that the formal sector tends to be more elastic to economic shocks (Altamirano et al., 2020; Esquivel, 2020; Moreno & Cuellar, 2021; Cuellar & Moreno, 2022). Concerning the secondary sector, its behavior is very similar to that of the tertiary sector, with an inevitable reaction to economic shocks derived from GDP.

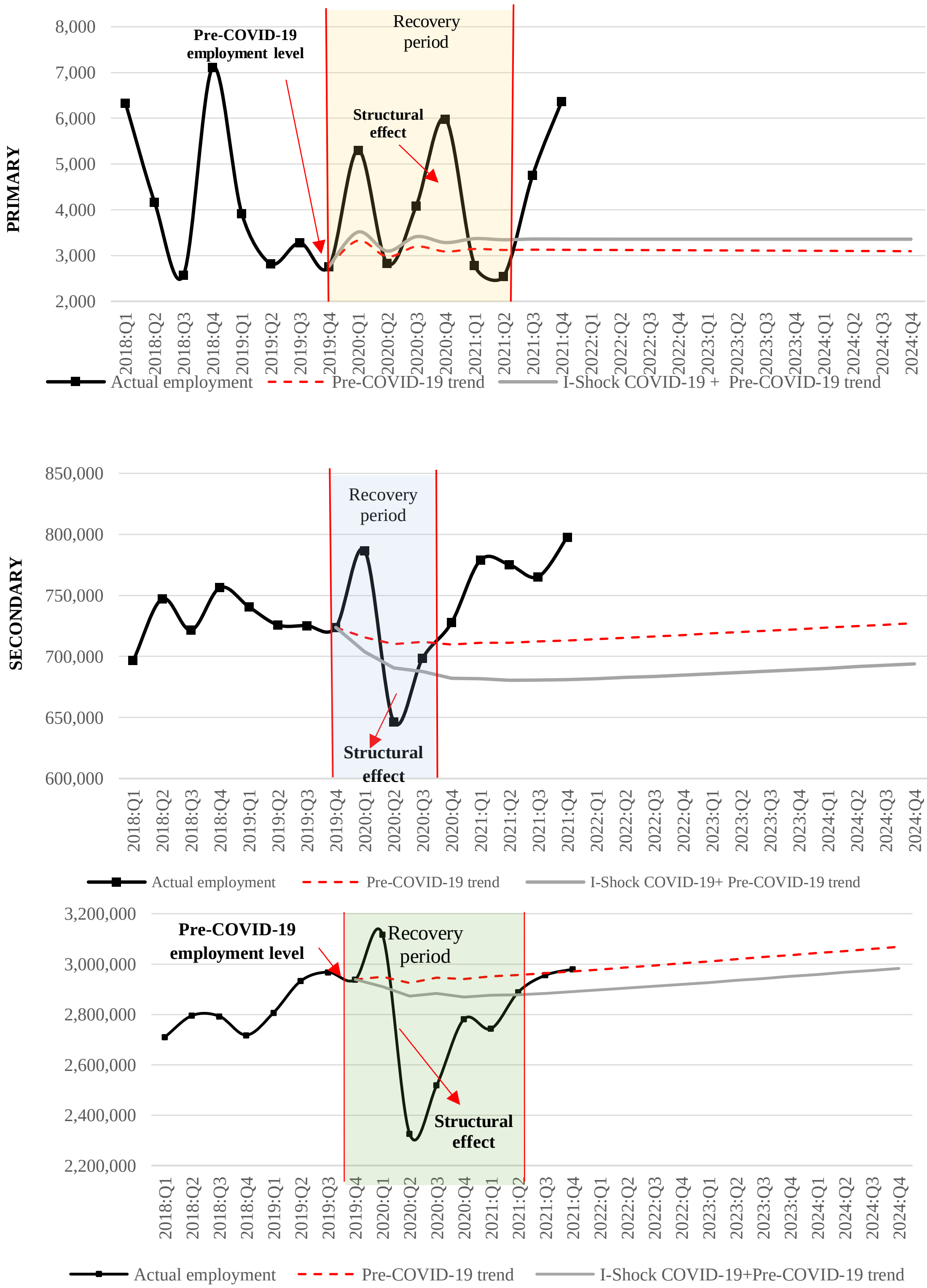
The second result is regarding the estimated cumulative job losses. The tertiary and secondary employment segments are the first step to study. The third and second graphs in Figures 2.1 and 2.2 show that the most profound impact (for both sectors and gender) was in 2020:Q2. The employment drop for the tertiary sector was -21% and -25% for men and women, respectively. Despite a sharp drop for men and women, the model suggests that current employment reached its "long-term" trend for men in 2021:Q1, while women lagged for one more period (2021:Q3). The secondary sector dropped by 15% and 18% (men and women). However, this sector recovered employment relatively faster than the previous one, which can be justified since the first shock impacted the tertiary sector. Then, like a chain reaction, the others were affected (Esquivel, 2020). Finally, acyclical behavior is observed in primary employment. Our model suggests that employment for men and women does not react to the impacts or shocks of the Mexican economy.

Figure 2.1 COVID-19 shock and men's employment by sector (Primary/Secondary/Tertiary)



Source: Own estimations with time series constructed and homologized of employment surveys (ENEU-ENE-ENOE).
Notes: trend estimation uses a VAR model. The data on employment observed in the second 2020 quarterly was calculated by ETOE.

Figure 2.2 COVID-19 shock and women's employment by sector (Primary/Secondary/Tertiary)



Source: Own estimations with time series constructed and homologized of employment surveys (ENEU-ENE-ENOE).
Notes: trend estimation uses a VAR model. The data on employment observed in the second 2020 quarterly was calculated by ETOE.

The third result is long-term employment growth trends (red line in the graphs). The model suggests that the initial shock is more persistent in all segments for men than women, to the extent that no recovery in job creation is observed in the twenty forecast quarters (2020:Q1-2024:Q4).

The previous result seems counter-intuitive, but before the COVID-19 crisis in 2019:Q1, a public program called "Jovenes Construyendo el Futuro" was implemented, where young people were hired as apprentices for 12 months in exchange for a scholarship in different companies across the country. Unfortunately, the ENOE, in its fundamental questionnaire structure, has no way to identify these temporary jobs, so the seasonally adjusted series could be affected by arbitrarily inflating the creation of structural jobs during this period.

This program may have temporarily inflated structural job creation during the 2019 crisis. So also, the recovery of structural jobs (current job series) could be overestimated during the crisis in the 2020-2021 period derived from this phenomenon.

Given the above two points, the long-term estimates suggest a slight downward trend and stability would reflect the Mexican economy's underlying conditions. There has been no growth in GDP per capita, and the employment growth could only be due to the trend in employment. Therefore, the observed trend is the fall toward the data's natural growth equilibrium state.

2.6 Concluding remarks

This chapter analyzes the deepening and persistence of employment losses by gender and industrial sectors, showing the recovery trends in each market segment. To pursue this objective, the research builds a consistent micro-founded time-series framework for the primary employment variables using quarterly data from 1993 to 2019 and following the same urban areas. As proposed by Cuellar (2019) and Moreno and Cuellar (2021), this methodology permits consistently defining and measuring all relevant dimensions directly from each micro data set in urban employment surveys in Mexico.

For pursuing the identification of employment structural trend components, the research estimates a VAR model linking each employment segment and aggregate production (defined by the real GDP) following the theoretical framework by Arrow et al. (1961) as proposed in Moreno and Cuellar (2020). This approach permits estimating long-run trends and short-run components in the segmented labor market. Then, the structural impact of the pandemic is estimated when considering the pre-COVID-19 forecasting of employment dynamics, given the initial observed shock on productivity, and compared with the actual employment levels observed over the year 2020. This approach allows for identifying the deepening and persistence of the initial shock of the recession.

The results suggest a structural and persistent effect on employment losses with lengthy recovery on employment levels, particularly in the male segment, and a more significant recovery rate relative to female employment. On the other hand, employment in the tertiary sector is more reactive to the first COVID-19 shock than in other sectors. Similarly, the secondary industrial sector shows a similar but less pronounced reaction, so all observed job losses are related to a structural change in the labor market. On the contrary, primary sector employment is inelastic to the initial shock.

The estimated outcomes of this research also suggest that public policies that artificially increase job opportunities, such as "Jovenes Construyendo Futuro" (an "on-the-job training" scholarship to promote employment among young workers with no experience) prior to the COVID-19 crisis or the prohibition of outsourcing to force switching those employment to formal during the COVID-19 crisis does not have long-run effects on employment. In the case of Mexico, the forecasted long-run employment levels for men and women, once the trend and seasonality of the series are considered, show a stable pattern in all sectors, contrary to the rapid recoveries of the observed series. Hence, these recovery rates might combine the policy effects and changes in the industrial employment structure.

This chapter proves that notwithstanding the adverse effects of the COVID-19 pandemic and the observed job recovery, long-run employment "binds the market." Hence, fundamental structural changes might include drift levels even by changes in the market structure but must be driven by policies that promote productivity and gender equality in the long run and not policies that artificially increase employment in the short run.

CHAPTER III. COVID-19, formal employment by skill segment and the gender gap in Nuevo Leon: dynamic and persistent effects in the labor market[13]

3.1 Introduction

The year 2020 represented a significant challenge for global economies. In March of the same year, the World Health Organization (WHO) officially declared the COVID-19 pandemic. More than two-thirds of the world's countries were economically paralyzed as a result of this health crisis, with tourism being one of the leading sectors affected. For Mexico, this scenario was not favorable since the tourism sector represents one of the primary sources of income for the country (Esquivel, 2020). This situation caused economic uncertainty, accumulating at the beginning of the pandemic, more than half a million losses in the formal employment for the country (INEGI, 2020). Nonetheless, for the state of Nuevo Leon, the opposite happened; in August 2020, this state ranked second in terms of formal job recovery in Mexico, only surpassed by the state of Jalisco (Coparmex Nuevo Leon, 2020; ENOE, 2020).

According to the Population and Housing Census conducted by the National Institute of Statistics, Geography, and Informatics (INEGI) in 2020, Nuevo Leon was one of the seven most populated states in the country, with the Monterrey metropolitan area standing out as the second most populated urban area in Mexico. Hence, understanding the labor market structure in this state and its different segments will allow us to have a broader perspective on regional employment dynamics and their relationship with unexpected situations, such as those that occurred due to the COVID-19 economic crisis.

This paper analyzes the dynamics and persistence in the regional labor market of the state of Nuevo Leon as a consequence of the COVID-19 economic shock. We accomplish this study by segmenting the labor market by workers' skills and gender, allowing us to identify heterogeneous effects and changes across market structures. Defining heterogeneity between groups, particularly between gender, allows us to recover the

[13] Published chapter: Cuellar, C., & Moreno, J. (2022). The Structural Impact of COVID-19 on Employment: The Role of Skills and Gender in an Industrialized Local Economy. In *Business Recovery in Emerging Markets* (pp. 61-83). Palgrave Macmillan, Cham.

market structure, changes in these trends, and analyze long-term differentiated dynamics by labor market segment (Cuellar, 2019; Moreno & Cuellar, 2021). We construct micro-founded formal employment time series, which retrieves consistent and homologous regional aggregate data over time. These series are obtained directly from micro-data from employment surveys in Mexico. The aggregate data are quarterly from 1987:Q1 to 2020:Q1, focusing on the urban areas of Nuevo Leon. The urban areas represent more than 90 percent of the total employment of this dynamic region, the second largest after Mexico City, according to the 2020 Mexican Census by INEGI.

Employment is segmented as mentioned above (skill and gender-skill). With it, we define and estimate two VAR models that link each segment of formal employment with the state economic activity (defined by the ITAEE NL) to identify the depth and persistence of the first COVID-19 pandemic shock (defined as *I-shock* COVID-19). Once the models are estimated, we use the impulse-response function methodology to perform an impact analysis, introducing the first shock observed in the economic activity of Nuevo Leon. With this, we recover the employment growth trends if the pandemic had not occurred and the trend with the I-shock COVID-19. Once these trends are estimated, they are compared with the observed employment to identify the structural changes and the potential recovery period of formal employment for each segment.

This paper contributes to the economic literature in four aspects. First, this paper uses several homologous and consistent time series constructed from micro-data provided in all employment surveys for Mexico. Second, it is the first regional study that analyzes the particular dynamics of the *high-skill* and *low-skill* employment segments for the state of Nuevo Leon. Third, we estimate dynamic employment models for the gender-skills, identify heterogeneous impacts across segments, and estimate impulse-response functions to compare the observed employment structure with the employment trend originated by the I-shock COVID-19. Finally, this study estimates potential recovery periods for each segment of the regional labor market.

This paper is divided into five sections, including this introduction. The second section briefly analyzes previous findings related to the theoretical framework, regional labor market, and COVID-19 crisis. The third section presents the data and methodology proposed to study regional employment dynamics divided by skills and gender. The fourth section presents the results obtained from the study. The fifth section presents the conclusions and implications of the analysis.

3.2 COVID-19, Mexican labor market and formal regional employment

3.2.1 A theoretical framework of labor market

The relationship between the labor market, economic growth, and productivity has been a recurring topic of study since the last century (Schumpeter, 1934; Becker, 1965; Mincer, 1975). Different theories show the complex interrelationships and sources of endogeneity in the labor market, including the connection between unemployment and economic growth (Okun, 1962). For this study, a neoclassical theoretical framework proposed by Arrow et al. (1961) is used as a reference, in which elasticities of substitution are proposed to identify causal effects of productivity in the labor market.

Moreno and Cuellar (2021) use a neoclassical model approach. This framework assumes perfectly competitive markets, and where the production function is of CES-type, and there are factors of production, which are capital (K) and labor (L); also this function presents returns to scale (s) and ρ is a positive parameter that measures the elasticity of substitution, expressed in Equation 1. From the optimality conditions, it can be observed that the marginal productivity of both factors equals their market price, r, and w (Equation 2). Furthermore, following the mathematical notation of Akkemik (2007), taking logarithms from the labor's first-order condition, we obtain Equation 3.

$$Q = f(K, L) = \theta[\beta L^{-\rho} + (1-\beta)K^{-\rho}]^{\frac{s}{\rho}} \tag{1}$$

$$f'(K, L) = f_k = r, f'(K, L) = f_L = w \tag{2}$$

$$\ln L = \alpha_0 + \alpha_1 \ln Q + \alpha_2 \ln w \tag{3}$$

The parameters of the last equation (α_1 and α_2) show the expected effect on the labor market derived from economic activity and wages. This neoclassical theoretical framework allows us to recover the causal structural effects caused by the exogenous shocks " ε_t " derived from COVID-19 on the different segments of the labor market in the state of Nuevo Leon. The following section presents the data and methodology used to capture the expected effects on the labor market as mentioned above.

3.2.2 Regional employment and the COVID-crisis

The COVID-19 pandemic caused one of the world's worst economic crises, causing short-term losses and predicted long-term effects. According to the International Monetary Fund (2020), the global economy fell by around 3%, with a recovery forecast until mid-2021. These unfavorable economic scenarios result in negative impacts, especially in lagging economies like Latin America, in which project losses are around 3-4% (CEPAL, 2020). Mexico, despite being a leader in these economies, its recovery will depend on its capacity to react to the shocks that the effects of the COVID-19 pandemic may cause.

One of the first exogenous productivity shocks derived from the pandemic in Mexico was observed in the tourism sector (Esquivel, 2020) due to implementing the social distancing policy. Given this first exogenous shock, structural effects begin to be observed. Structural effects in economics are caused by the interrelationships between economic agents, which produce complex relationships, and these relationships cause different effects in the market (Sampedro & Cortina, 1969). In Mexico, three ways of structural effects were observed: supply, demand, and financial. Identifying these sources will allow us to understand the repercussions of these effects on the market, especially labor.

As Mexico is a labor-intensive country, understanding its dynamics and structure is fundamental to reactivate the Mexican economy. Some authors predicted employment losses for the country that fluctuate between 5-20% (Altamirano et al., 2020; Jimenez-Bandala et al., 2020; Maldonado & Ruiz, 2020; Nunez, 2020), each work with its respective study methodology, but all agree on the slow recovery of employment in the country, some of them predicting recovery by mid-2021 (Banco de Mexico, 2020; Mexico Como Vamos, 2020; Moreno & Cuellar, 2021). For the state of Nuevo Leon, the panorama was very different from the national one, since right in the middle of the pandemic, it

reported formal employment recoveries, placing it among the first states to achieve an early recovery of jobs (Coparmex Nuevo Leon, 2020; ENOE, 2020).
There is little literature studying the employment dynamics of Nuevo Leon related to the COVID-19 pandemic for this state. Sanchez (2020) makes projections of employment recovery for the northern border states, including Nuevo Leon; these projections observe recovery starting in the last quarter of 2020 and finally normalizing in the second quarter of 2021. On the other hand, the Centro de Investigaciones Economicas (CIE) forecasts an employment recovery in Nuevo Leon of 4.90% by the end of 2021 (Flores, 2021).

Accordingly, conducting a regional study for the state of Nuevo Leon contributes not only to the literature but also to understanding the dynamics and structure of the labor market in a state considered one of the country's leading economies. Therefore, the main contribution of our work is to allow for regional heterogeneity in the labor market, differentiating employment by gender and skills. This segmentation will allow us to analyze the impact of COVID-19 on formal employment in the state of Nuevo Leon and thereby estimate potential employment recoveries in the different segments of the market.

3.3 Data and methodology

3.3.1 Data

For the estimations, we construct micro-founded time series from all existing employment surveys for Mexico: Encuesta Nacional de Empleo Urbano (ENEU), Encuesta Nacional de Empleo (ENE), and Encuesta Nacional de Ocupacion y Empleo (ENOE). This methodology of construction and harmonized based on micro-foundations has been employed in previous works studying employment, and gender gap for the country are also analyzed (Moreno & Cuellar, 2021; Cuellar & Moreno, 2021). The construction of this long-run database makes it possible to control both inclusion and exclusion biases that may exist due to the data structure and other structural changes. Moreover, with this approach and model choice, micro-founded time series are recovered, allowing us to study them in a consistent time macro-time-series perspective.

The ENEU, ENE, and ENOE are published by INEGI and capture data on employment and sociodemographic characteristics of a representative sample of individuals in this country. Employment microdata is public for all surveys, and the publication periods are quarterly. For the ENEU, the available periods are from 1987 to 2004, for the ENE 1988 to 2004, and the ENOE from 2005 to date. These surveys are a dynamic panel; they include the same individual for five quarters and alternate each quarter to 20% of the sample.

For this research, we take advantage of the characteristics of cross-sectional data to construct quarterly aggregate data for Nuevo Leon from 1987:Q1 to 2020:Q1, that is, quarterly employment time series, because we are interested in obtaining the behavior in the aggregate of these series. To estimate the implied pre-COVID19 forecasted trend in employment, we decided to use ENOE before the pandemic and later apply the parameter estimation of long-run trends to compare the actual values of the ENOE post-COVID-19 to the implied estimation. This choice was to have a pre-pandemic structural model to build a counterfactual trend and then identify the structural change due to the pandemics by comparing this trend to the actual observed values.

In this study, we are interested in recovering the structure of the labor market segmented by skills and gender. Therefore, the following time series are constructed: *low-skill* employment, *high-skill* employment. And then, we construct time series by skill-gender: *low-skill* male employment and *low-skill* female employment, *high-skill* male employment, and *high-skill* female employment.

According to the above, the terms *high-skill* and *low-skill* must be defined; for this study, the ability is measured through the level of schooling achieved by the worker (Werner et al., 2021). Therefore, individuals with basic education (primary and lower secondary) or less educational level are classified as *low-skill* employment. In contrast, individuals with technical, high school, undergraduate, or graduate education are considered *high-skill* employment. Since we will link employment and regional economy, we use the Quarterly Indicator of State Economic Activity (ITAEE) for Nuevo Leon. This series is obtained directly from INEGI. Furthermore, the last series to be constructed is the real average hourly wages from employment surveys.

Based on the facts described above, the construction of the time series of employment and wages is limited to the employment growth rates for this research. The final sample consists of individuals between the ages of 16 and 65 working and receiving a monetary payment greater than zero, excluding individuals who work informally without receiving any payment or remuneration. Formal employment is that individual who has social security. In employers, subcontractors, and self-employed workers, it is decided to reference the number of workers employed and whether the company name is registered (Moreno & Cuellar, 2021; Cuellar & Moreno, 2021). For the analysis, six time-series are constructed at the regional level (Nuevo Leon) and removing the seasonal factor and are presented as growth rates. Finally, all rural areas of Nuevo Leon are excluded from homologating both databases since the ENEU only includes urban areas of Mexico.

3.3.2 Empirical strategy

Since we want to analyze the relationship between economic activity and employment, this study takes as a reference a dynamic neoclassical model of labor market equilibrium, which allows us to study the relationships between production, productivity, employment, and wages (Arrow et al., 1961; Akkemik, 2007).

This model allows us to estimate the causal impact of the economy on employment, so this theory will allow us to propose an empirical model with simultaneous interactions between these variables. The econometric methodology proposed is Vectors Auto-Regressive (VAR) in reduced and unrestricted form. This method allows us simultaneity between variables and helps us find persistence between the same series, in the long run, with the correct specification of the lags. Moreover, since the technique does not impose restrictions on the model, it avoids specification errors (Sims, 1980).

Two models are estimated for this study. The first model studies the dynamics of formal employment by skills and economic activity in Nuevo Leon (Model 1). The time series of interest are represented in growth rates, where y_{1t} is *low-skill* employment, y_{2t} *high-skill* employment, y_{3t} is the ITAEE NL and y_{4t} the real hourly wage. For the second model (Model 2), skill employment is segmented by gender, so this model contains six variables, where y_{1t} is *low-skill* male formal employment, y_{2t} is *low-skill* female formal employment, y_{3t} is formal employment *high-skill* men, y_{4t} is *high-skill* female formal employment, y_{5t} is the ITAEE NL and, finally, y_{6t} the real hourly wage.

Each vector has its respective autoregressive component ($t{-}p$), and a component associated with the white noise process, ε_t. The reduced VAR model can be represented in terms of its characteristic polynomials defined over the number of "L" lags, $a(L, \phi)$ *and* $b(L, \theta)$, as follows:

$$y_t = a(L, \phi) y_{t-p} + b(L, \theta)\varepsilon_t \tag{4}$$

$$a'(L, \phi) y_t = b(L, \theta)\varepsilon_t \tag{5}$$

Given the time stability of the series distribution, we could represent in terms of the Gaussian white noise process, as Equation 6. The new characteristic polynomial $c(L, \phi, \theta)$ is unique for each VAR process defined over the number of lags (L), and we used the maximum likelihood method through the properties of the Gaussian process to recover the parameters associated with the original model, $\{\phi, \theta\}$.

$$y_t = \frac{b(L, \theta)}{a'\,(L, \phi)}\varepsilon_t = c(L, \phi, \theta)\varepsilon_t \tag{6}$$

In addition to this model, since the objective is to analyze the impact derived by the COVID-19 I-shock, each respective model's Impulse-Response Functions (IRF) are estimated. The IRFs allow capturing the reaction of the model variables to an unanticipated "shock" in the error component of the model (ε_t). Information is obtained from the variance decomposition of the orthogonal error term on the random innovations of each endogenous variable belonging to each model. Once the IRFs are obtained, where the impulse is in economic activity (ITAEE NL) and the response is in employment, everything is retrieved regarding employment levels to compare pre-COVID-19 trends, *I-shock* COVID-19 trends, and observed employment structure.

3.4 Estimation and results

The study's objective is to analyze and recover long-term employment trends in Nuevo Leon. Once these estimates are obtained, they are compared with the employment structure observed up to the most recent data (2020:Q4). To study the dynamics and structure of employment, we divide the analysis into three time series:

- *Pre-COVID-19 trend*: these time-series forecast employment levels using the long-run estimates without any shock; namely, this would give us the expected level of employment if COVID-19 crises had not happened.
- *I-shock COVID-19 + Pre-COVID-19* trend: these time-series forecast employment levels given the first shock due to the crises (ITAEE NL) and the respective trend from this impact.
- Actual employment: theses series show us the employment levels observed for the Nuevo Leon state on each market segment.

With these forecasted time series, we can recover the *counterfactual gaps* on long term employment by market segments as follows:

- Pre-COVID-19 vs. post-COVID employment long-run trend.
- Pre-COVID-19 vs. observed employment trend.
- Post-COVID-19 vs. observed employment trend.

In other words, the counterfactual gaps allow us to do a hypothetical framework in the labor market. It helps to explain what would happen if the COVID pandemic had not occurred and compared it with all the other scenarios.

To estimate trends and gap impact, we introduce a negative shock equivalent to the observed impact of COVID-19 crises over ITAEE NL through the IRFs. Moreover, the VAR model will estimate the pre-COVID-19 trend, differentiating what would have been without the pandemic. Finally, the observed employment captures the magnitude of the structural effects. With this, we can project scenarios of potential recovery in the different employment segments in the state of Nuevo Leon.

First, unit root tests and optimal lag tests are performed to confirm the statistical validity and stability of the VAR models. Then, the employment impact analysis is presented, in which the Impulse-Response Functions are presented. With them, the trends, pre-COVID-19 and *I-shock* COVID-19, are estimated for each model (Model 1 and 2) and compared with the structural effects of observed employment.

3.4.1 Unit root test and selection criterion optimal lags

The time series are presented in growth rates, so two types of unit root tests were performed: Augmented Dickey-Fuller (ADF) and Phillips-Perron unit root test to test the series's stability in the long term. Table 3.1 presents the stationarity tests for the ITAEE, the employment segments, and the real hourly wage. It is observed that all series are stationary in both tests, so these series are consistent with order-one I(1) data.

Once the statistical validity of the time series is confirmed, a model fitting must be performed to perform the impact analysis. This study uses an unrestricted VAR model, so a critical point is the order of the variables and the optimal number of lags to be used in the models. For this analysis, we take the basis of the theoretical model to order the variables as follows: employment-ITAEE NL-real wages.

According to the order of variables implemented, we proceed to estimate five optimal lag criteria, from which we must choose which criterion we are going to keep. Table 3.1 presents the statistics associated with the selection of the optimal lag for both models. We test six criteria to choose the optimal lag for the model: Log-likelihood (LL), Likelihood ratio (LR), Final Prediction Error (FPE), Akaike's Information Criterion (AIC), Hannan and Quinn Information Criterion (HQIC), and Schwarz's Bayesian Information Criterion (SBIC). Table 3.1 shows that two groups (LL, LR, FPE, AIC, HQIC) propose that one lag and (SBIC) propose that it should be 0 lag. According to the literature, it will be proposed that the model should have one lag, given the size and periodicity of the series (Ivanov & Kilian, 2005). This criterion is applied in both models, and once the criterion is selected, we perform the employment impact analysis.

3.4.2 Employment impact analysis: the I-shock COVID-29 and structural effect

Given the nature of the models and the high multicollinearity among the variables, it is not recommended to make individual inferences of the estimators (Akkemik, 2007), so the model is reported in the annexes for information (Figure A.3). Focusing on the dependent variables of interest will help us analyze the behavior after introducing the I-shock COVID-19. This section presents the main contribution of our research, which is to recover and quantify the impact of the I-shock COVID-19 on the employment of skills in Nuevo Leon.

Table 3.1 VAR model: tests and selection criteria

Z-statistics for hypothesis testing unit roots

Growth rates	**Augmented Dickey-Fuller (ADF)**		**Phillips-Perron Test (PP)**	
PIB	-7.93	***	-78.05	***
ITAEE	-8.94	***	-95.33	***
Low-skill employment	-11.709	***	-140.22	***
High-skill employment	-11.206	***	-125.24	***
Real wage per hour	-17.63	***	-172.41	***
Men				
Low skill employment	-11.45	***	-132.42	***
High skill employment	-12.65	***	-141.45	***
Women				
Low skill employment	-14.05	***	-159.39	***
High skill employment	-11.82	***	-124.58	***

Selection criterion for optimal lags in VAR models

Model 1: Employment skills

Lag	**LL**	**LR**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	868.161		1.60E-11	-13.5025	-13.4663	**-13.4134***
1	895.379	**54.435***	**1.3E-11***	**-13.6778***	**-13.4967***	-13.2322
2	907.724	24.691	1.40E-11	-13.6207	-13.2948	-12.8186
3	918.474	21.499	1.60E-11	-13.5387	-13.0679	-12.38
4	930.731	24.515	1.70E-11	-13.4802	-12.8646	-11.965

Model 2: Employment gender-skills

Lag	**LL**	**LR**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	1187.34		3.90E-16	-18.4584	**-18.4041**	**-18.3247**
1	1232.79	90.904	**3.3E-16**	**-18.6061**	-18.2258	-17.6702
2	1263.62	**61.662**	3.60E-16	-18.5253	-17.8192	-16.7874
3	1286.99	46.745	4.50E-16	-18.328	-17.296	-15.7879
4	1310.05	46.106	5.60E-16	-18.1257	-16.7677	-14.7835

*p-value: 0.01***, 0.05**, 0.10*.*
Source: Own estimations with time series constructed and homologized of employment surveys (ENEU-ENE-ENOE). Seasonally adjusted series presented by growth rates.

Notes: Sample 128 observations. LL: log-likelihood, LR: likelihood ratio, FPE: final prediction error, AIC: Akaike's information criterion, HQIC: Hannan and Quinn information criterion, SBIC: Schwarz's Bayesian information criterion.

Once the structure of skills employment (*low-skill* and *high-skill* employment) is analyzed, we segment the labor market by gender to understand the labor market dynamics. To estimate the impact, we rely on Impulse-Response Functions, using economic activity (ITAEE NL) as the impulse variable, and the response variables are the different segments of the labor market. For Model 1, the response variables are Nuevo Leon's *low-skill* and *high-skill* formal employment. For Model 2, these skill segments are divided by gender, so the response variables are *low-skill* male and female employment and *high-skill* male and female; all segments belong to formal employment.

For both models, we introduce as *I-shock COVID-19* the observed change in economic activity (ITAEE NL) of Nuevo Leon for the second quarter of 2020, which was -21% (INEGI, 2020). The magnitude of the impulses in the IRFs is introduced in one standard deviation, so a 21% drop had to be converted in standard deviations for the models, a magnitude of -2.14 standard deviation (s.d.). Figure A.3 present the Impulse-Response Functions of each model differentiated by skill-employment structure (Model 1) and gender-skills (Model 2).

It can be seen in Figure A.2 that both formal employment structures in Nuevo Leon decline in the face of the negative impact of the COVID-19 I-shock in the short-run (period t+1), as estimated in several sources for IMSS registered workers (Banxico, 2020). On the other hand, our estimation shows that, if we segment by skills, employment loss is differentiated, with *high-skill* employment being more reactive (15% drop) relative to *low-skill* employment (1.6% drop), but with greater adjustment capacity, i.e., *high-skill* employment recovers faster from the *I-shock*. As for Figure A.3, both genders show independent dynamics, with women being more inelastic to the COVID-19 I-shock, while men are more reactive to it. The shock for men was more profound for the *low-skill* employment (2.1%), while *high-skill* employment presents potential rapid recovery (2020:Q4).

Female employment presents a different dynamic to male employment since *high-skill* employment is observed more significantly. In contrast, *low-skill* employment seems to be inelastic to this COVID-19 I-shock. While for the *low-skill* represented a decrease of .2%, for *high-skill* it was 1%.

These impulse-response functions allow us to recover the trend with the *I-shock* COVID-19 in employment in Nuevo Leon, and with the support of the models, we estimate the pre-COVID-19 trends. Once these trends are estimated, in the next section, we append the employment observed in the four quarters of 2020. We can differentiate between the employment losses derived from the I-shock and the losses derived from the structural effects triggered by the COVID-19 shock.

a) Formal employment by skills

As other authors have previously analyzed (Altamirano et al., 2020; Esquivel, 2020; Moreno & Cuellar, 2021), formal employment tends to be more elastic to economic shocks. This study introduces a negative I-shock derived from the COVID-19 shock through the economic activity indicator for Nuevo Leon (ITAEE) and recovers skill employment losses by comparing the observed employment level and the different trends (pre-COVID-19 trend and *I-shock* COVID-19 trend).

Figure 3.1 shows the cumulative loss of skills employment in Nuevo Leon, compared to employment trends, respectively (one without COVID-19 shock and the other including it). Three series can be identified in the figure; in black with dots, the first represents observed employment obtained from the ENOE for the sample. Only the second quarter of 2020 was calculated from the Encuesta Telefonica de Ocupacion y Empleo (ETOE), this being an extension of the previous survey due to the months of confinement. The red dotted line estimates the long-run employment growth trend (pre-COVID-19 non-crisis situation); this was estimated from the VAR Model 1. Finally, the gray line is the trend recovered from introducing the negative I-shock COVID-19 in the impulse-response function and adding the long-run growth trend to it.

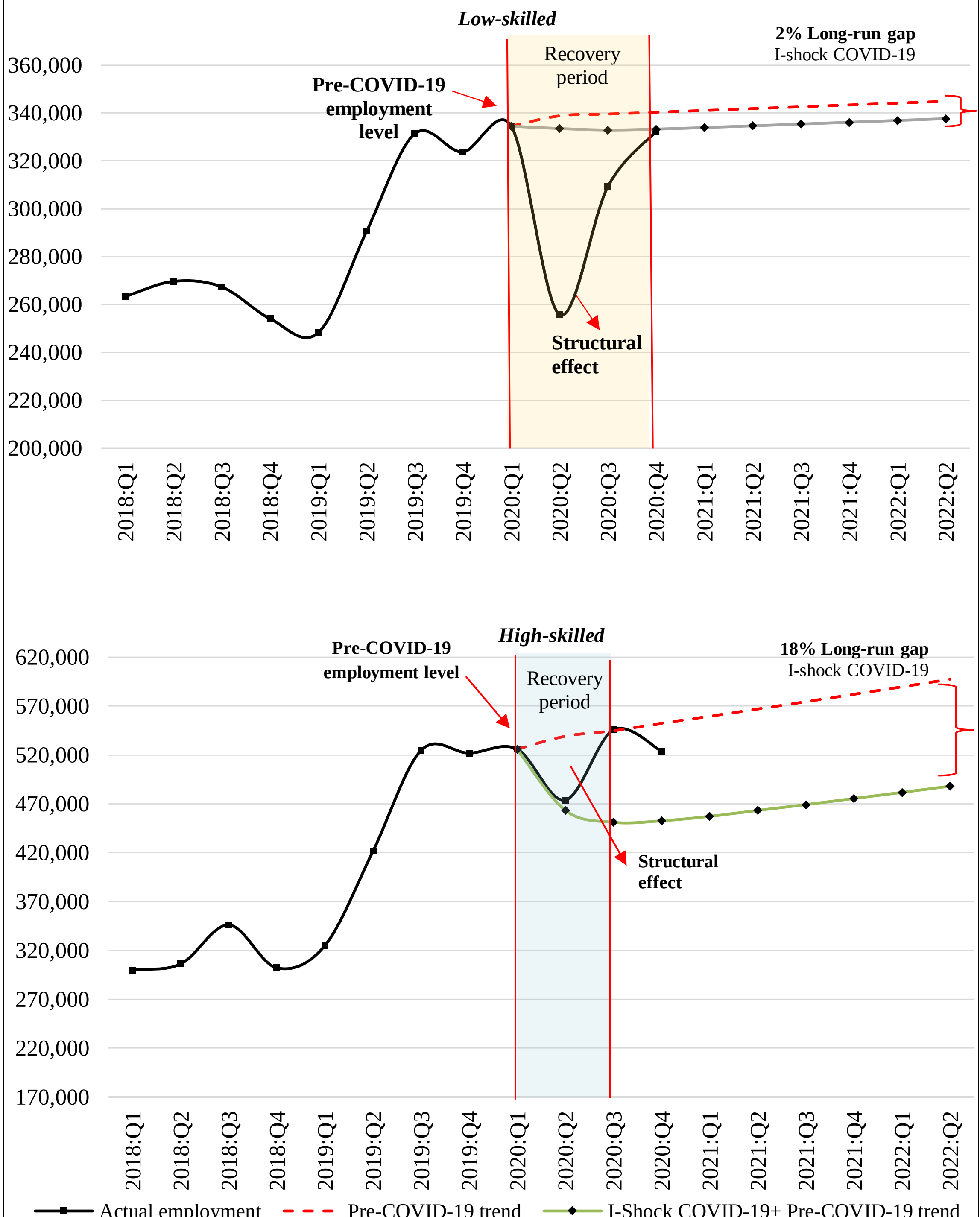
The most profound employment loss for the state of Nuevo Leon was in 2020:Q2, which is somewhat different from the dynamics presented for the country, as by 2020:Q3 Mexican formal employment reported its lowest levels (Moreno & Cuellar, 2021). In percentage terms, the drop in *low-skill* employment in 2020:Q2 represented a loss of 23%, while *high-skill* employment fell by only 9% in the same period. Figure 3.1 shows that the I-shock COVID-19 created a long-term employment gap of 2%. According to the latest 2020:Q4 *low-skill* employment observation, there are still permanent job losses for the state. In levels, these losses represent almost 9 thousand *low-skill* jobs.

Regarding the *high-skill* labor market (Figure 1), the COVID-19 I-shock originated an 18% gap in long-term employment. However, given that this employment segment is more dynamic and adjusts more rapidly, the gap is reduced to only 5% concerning the last observation. Two effects are observed in *high-skill* employment levels, one of the gains and one of the losses. Almost 72 thousand *high-skill* jobs were gained compared to the I-shock COVID-19 trend, while for the pre-COVID-19 trend, there are still losses of about 28 thousand *high-skill* jobs in the long run.

b) Formal employment by gender-skills

Employment in Nuevo Leon represents one of the main strengths since, in mid-2020 when employment seemed to have collapsed in the country, this state was one of the best entities in terms of employment recovery, only behind Jalisco (Coparmex Nuevo Leon, 2020). For this reason, understanding the dynamics of employment will lead us to a better understanding of the market, so segmenting employment by skills and gender could provide us with some structure of the labor market in the region. For the case of Latin America, the International Monetary Fund (2021) found that *low-skill* employment was the most adversely affected during the second quarter of 2020, presenting decreases, mainly in female employment. On the other hand, *high-skill* employment also shows losses, but the recovery is faster than *low-skill* employment.

Figure 3.1 COVID-19 shock and formal labor employment in Nuevo Leon, by skill level



Source: Own estimations with time series constructed and homologized of employment surveys (ENEU-ENE-ENOE).
Notes: trend estimation uses VAR Model 1. The data of employment observed of 2020:Q2 was calculated of ETOE.

The following section is divided into two parts; the first presents the structure of the *low-skill* market and its gender differences, and the second, the *high-skill* market for men and women. Figure 2 shows the dynamics of *low-skill* employment for men and women in Nuevo Leon; the first thing to note is the peculiar behavior of both structures. Men in 2020:Q2 show a 53% drop, while in female employment, the opposite is observed since, for this same period, the observed employment increased by 33%. In the literature, this behavior of the labor market between genders is known as the "substitution effect," which responds to the hypothesis that in times of economic crisis, the female labor market functions as a driver of employment, i.e., it increases, as opposed to male employment, which decreases (Humphries, 1988; Skoufias & Parker, 2006; Gomez & Mosino, 2019).

The COVID-19 I-shock was also differentiated between genders, while it originated a 3% gap for men. For women, it represented a 1% gap for the pre-COVID-19 employment trend. This phenomenon could be translated in terms of elasticity, i.e., female employment was more inelastic relative to male employment in the face of this first economic shock.

In terms of employment levels, this crisis represented an increase in female employment as it reports a gain of just over 1 thousand *low-skill* jobs over the pre-COVID-19 trend, while men still show permanent job losses of almost 10 thousand over the same trend. Finally, it is worth noting the speed in the adjustment dynamics while for women, two quarters was enough to adjust and overcome the long-term growth trend in employment (pre-COVID-19 trend). For men, two quarters was not enough. According to the latest available observation, they continue to present permanent losses of *low-skill* employment (2020:Q4).

Figure 3.2, also shows the structure of *high-skill* employment by gender. This employment segment is very similar to the *low-skill* segment, where the gender effect is a proxy. In 2020:Q2 male employment presented a drop of about 26%, and female employment increased 13% for this same period. Regarding the COVID-19 I-shock, both the male and female segments are more reactive to shocks than the *low-skilled*. For *high-skill* male employment, this first shock represented a 10% gap compared to the pre-COVID-19 gap.

This gap was relatively minor for women, representing only a 2% gap compared to the non-pandemic employment growth gap.

The employment levels presented for both groups are in negative figure, with men reporting a loss of *high-skill* employment of a little more than 24 thousand jobs compared to the pre-COVID-19 trend. In comparison, women only lost around 2 thousand jobs compared to the same trend. In *high-skill* employment, the recovery dynamics for men represent a problem since, despite being a dynamic employment structure, there are still permanent losses concerning their last observation, so a recovery period cannot be defined. As for female employment, the recovery is observed in 2020:Q4 in Figure 3.2 below.

Finally, the above results show decreases in the gender employment gap for the state of Nuevo Leon as a result of structural employment dynamics. The COVID-19 pandemic represented an opportunity in favor of labor market integration for Nuevo Leon women. The crisis decreased the relative gender employment gap observed in the state by seven percentage points for *high-skill* employment and by two percentage points for women's *low-skill* employment. In 2020:Q1 (pre-COVID-19), the relative *high-skill* employment gap between genders was 34%, while in 2020:Q4, the gap was 27%. For the same period, the relative employment gap between gender for the *low-skill* market was 51%, while in the end, it was 49%. The main relative gains associated with the gender gap are integrating women in the high skill segment and job substitution favoring women in low skill due to the estimated dynamics in the first segment.

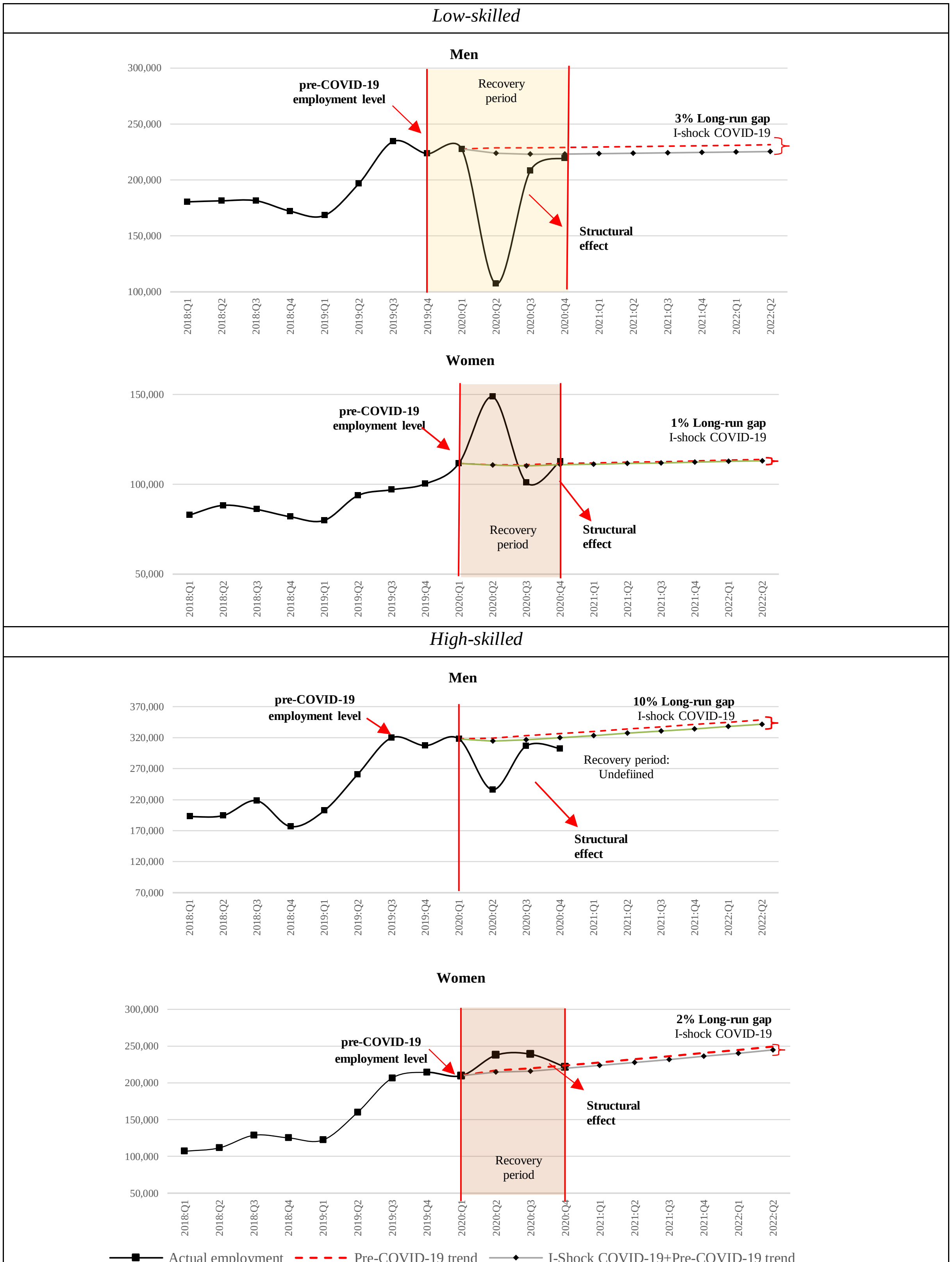
3.5 Concluding remarks

In this study, we analyze the depth and persistence of employment losses by skill and gender-skill for the state of Nuevo Leon, trying to identify structural changes during the COVID-19 pandemic. We use quarterly data for 1987 to 2020 and construct a consistent, micro-founded employment time series for each labor market segment from employment surveys for Mexico. Two VAR models are defined, linking each labor market segment (skills and gender-skills) and the state's economic activity (ITAEE NL) by gender.This method allows recovery trends (pre-COVID-19 and I-shock COVID-19) to analyze observed employment losses compared to both trends.

The main results show differentiated impacts on employment; according to the different segments analyzed, *high-skill* employment is more reactive than *low-skill* employment, so employment recovers faster. Recovery takes about six months for the *high-skill*, while it takes about one year for the *low-skill*. On the other hand, if we segment skill employment by gender, we observe gains in observed employment, resulting in decreased relative employment gaps and a more significant proportion for *high-skill* employment; these gender employment gaps represented about seven and two percentage points *high-skill* and *low-skill* respectively. The limitation of this study is that the analysis only focuses on the formal labor market in urban areas of Nuevo Leon, as this allows us to identify the long-term impacts on these market segments more accurately.

The implications of this analysis allow us to understand the regional employment dynamics derived from the COVID-19 crisis, highlighting the importance of designing public policies in favor of investment in human capital, as proposed by classic economic theories (Schultz, 1961; Becker, 1965; Heckman, 2012). On the other hand, for gender public policies, more significant opportunities in the state translate into greater female labor participation. One important feature is that the women labor market shows an impressive counterintuitive structural dynamic behavior. In particular, women's employment for both high-skilled and low-skilled segments shows the creation of employment during the COVID19 pandemic for the state.

Figure 3.2 COVID-19 shock on employment in Nuevo Leon, by skill level and gender



Source: Own estimations with time series constructed and homologized of employment surveys (ENEU-ENE-ENOE). Notes: trend estimation uses a VAR model. The data of employment observed of second 2020 quarterly was calculated of ETOE.

These findings present an interesting additional fact: the access to the internet and technological infrastructure that predominates in Nuevo Leon might have played a fundamental role in the insertion and transition of women in the labor market, as we observed for the case of the high skilled segment. Thus, employment gender gaps are reduced naturally by each of their market dynamics. Adjustments are given human capital levels without implementing policies that distort market prices (*enforced minimum wages*) or impose gender quotas (*affirmative actions and contracts*).

Allowing for heterogeneity among human capital at the regional level permitted us to identify the differentiated behaviors among segmented labor market groups and analyze the existing structural changes derived from the current COVID-19 pandemic. In conclusion, this study allows us to understand the dynamics of employment in the state of Nuevo Leon, mainly the dynamics between the different employment segments and gender, so that more and greater access to employment opportunities for women would allow an accelerated recovery of the labor market in the state. Even so, one of our primary concerns is understanding the dynamics of employment by skills across the different states of Mexico. Therefore, for future analyses, we propose extending the study of employment dynamics across the country's states. Also, analyzing the investment in technology and infrastructure could help us better understand employment dynamics, integrating women into the formal sector, particularly in the high-skilled and higher wages sector.

GENERAL CONCLUSIONS

Gender economics in Mexico is a line that several academics have explored in the country. However, there is a lack of studying these issues from a microeconomic and time historical approach. Therefore, one of the main contributions of this work was to achieve a historical analysis of gender from a microeconomic perspective and also annex one of the events that have most impacted the world economy in recent times, COVID-19.

For this study, we use quarterly public surveys for Mexico from 1988 to 2019, such as the ENEU, ENE, and ENOE, which INEGI publishes. The construction of homologous series, which are comparable over time, allows us to recover some of the parameters associated with the study of socioeconomic problems in Mexico, one of them being wage gaps, as well as to recover the dynamics of the labor market between genders by skills or by sectors when there are exogenous shocks such as the COVID-19.

Concerning economic theory and econometrics, we start with neoclassical models of human capital, which are based on individual decisions regarding labor supply and wages. These decisions are impacted by variables such as education, occupation, sector, gender, marital status, and work experience, among others (Becker, 1965; Mincer, 1975; Ben-Porath, 1967; Blinder, 1973; Oaxaca, 1973 and Mulligan & Rubinstein, 2008). In addition, it corrects one of the main economic problems when analyzing wages: self-selection bias (Heckman, 1977).

The main limitation of this work is related to the sample. We only include the first sixteen metropolitan areas from the first to the last survey analyzed. These allow us to have comparability over time. However, on average, we are left with about 60% of the sample for the analysis.

In general, the hypotheses put forward and demonstrated in this doctoral thesis are as follows:

a) **Both men and women show an increasing trend in the average years of schooling, but the wage gap persists in favor of men in Mexico.**

First, it was shown that, in the last thirty years in Mexico, the relative labor supply of women has increased compared to men. In addition to the fact that more women are in the labor market, there are more educated women since they have more schooling than men on average.

In the last 20 years, average educational attainment has decreased for both genders, but the decrease is more significant for men. Finally, the gaps persist in favor of men, even though women are more educated. On the other hand, there are unobservable factors, such as selection bias, which explains about 50% of the gender wage gap in Mexico.

b) **The economic shock derived from COVID-19 was more reactive for the third sector than the other sectors. At the same time, the primary sector labor market is inelastic for both genders in Mexico.**

The economic shock from COVID-19 significantly impacted the employment structure in Mexico. The effect is persistent in terms of job losses, and the recovery was slow, particularly for men, while for women, the recovery was relatively faster.

On the other hand, the tertiary sector labor market turned out to be more reactive to the first shock than the other sectors. Similarly, the secondary sector labor market reacts to the first shock of the pandemic, but the recovery is less pronounced. On the other hand, the opposite is true for the primary sector labor supply, which is inelastic to the first COVID-19 shock.

c) **The economic shock derived from COVID-19 had a differentiated impact on the regional labor market. Specifically, in Nuevo Leon, the low-skill labor supply (measured in terms of schooling) was more affected by the shock than the high-skill labor supply.**

Regional employment had differentiated impacts derived from the first COVID-19 shock. First, high-skill labor supply is more reactive to low-skill labor supply, allowing for a relatively faster recovery in employment levels.

When dividing employment by skill and gender, Nuevo Leon specifically experienced a decrease in the relative employment gap in high-skill jobs as more high-skill women entered the labor market due to the pandemic. At the same time, low-skill jobs of both genders were affected by this shock.

Finally, the results suggested by this doctoral thesis allow us to draw conclusions focused on gender public policy in Mexico. Mainly, this work explores in detail the dynamics differentiated by gender, skills, and sectors in the Mexican labor market, so it is observed that the differences are not merely discriminatory but structural. Therefore, understanding the structure of each labor market segment would allow us to establish policies that do not distort the price market (enforced minimum wages) or impose gender quotas (affirmative actions and contracts). Furthermore, for future lines of research, it is proposed to extend the study of the gender labor market by showing differences between groups and intra-groups since the heterogeneity that may exist between these groups could be a significant part of the differences between men and women.

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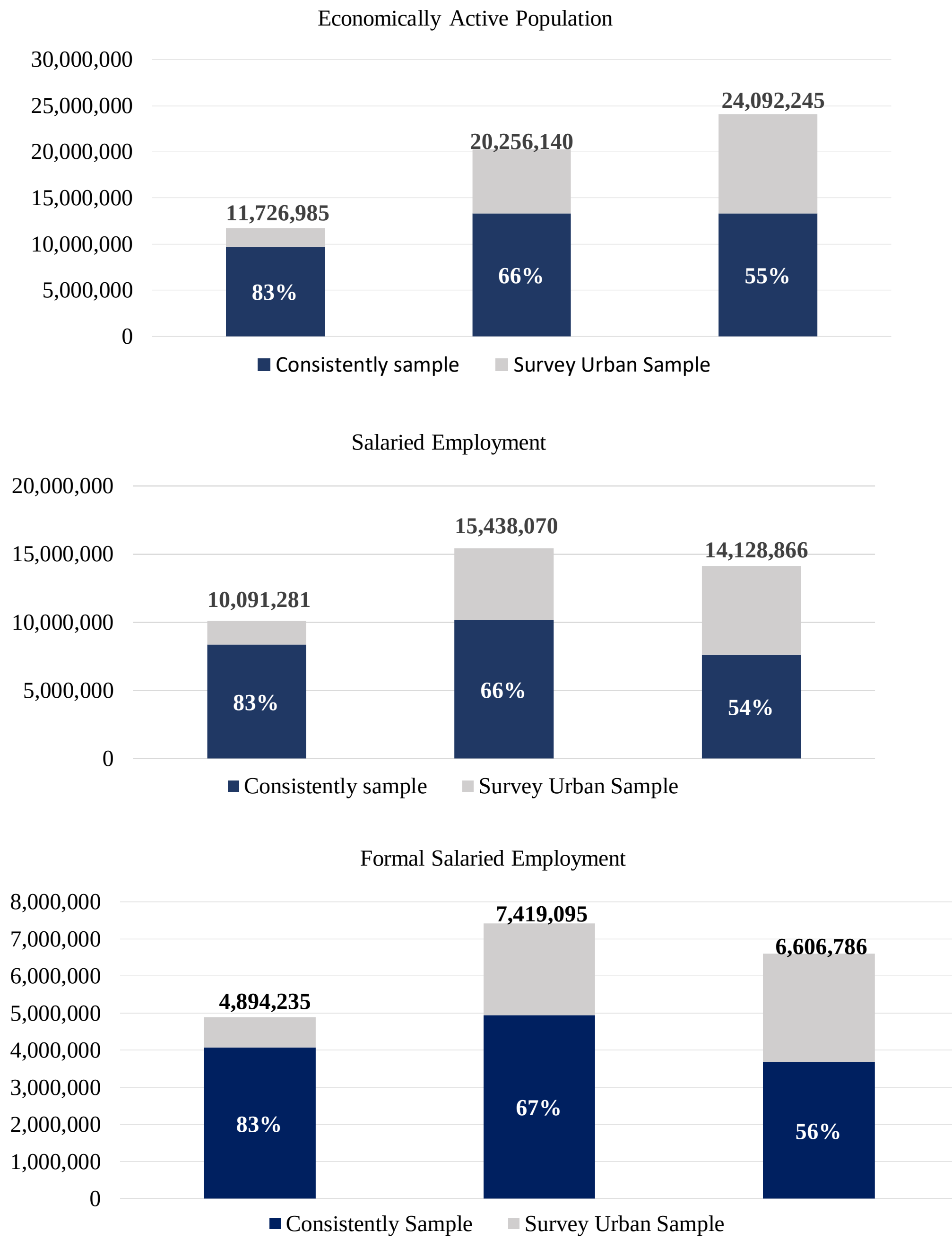
APPENDIX

This appendix shows the composition of three main labor market variables: economically active population, salaried employment, and formal salaried employment. These figures show how much our subsample equals in proportion to the entire employment survey sample population.

Figure A1. Harmonized employment surveys for Mexico



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

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 also presented.

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

		Women			Men		
		Returns to Schooling		Self-selection bias	Returns to Schooling		Self-selection bias
		Corrected	Uncorrected		Corrected	Uncorrected	
1988	I	5.76	5.52	10.1	6.08	6.05	-53.0
	II	5.87	5.62	11.8	6.13	6.15	-48.4
	III	6.52	6.37	9.1	6.74	6.53	-61.8
	IV	6.01	5.78	9.6	6.64	6.52	-66.8
1989	I	6.11	5.89	9.5	6.47	6.47	-60.2
	II	6.19	5.96	9.9	6.41	6.56	-49.5
	III	7.24	7.10	11.0	6.70	6.56	-72.3
	IV	6.98	6.64	15.4	7.03	7.02	-86.2
1990	I	6.57	6.23	15.0	7.31	7.35	-86.1
	II	6.58	6.35	9.0	7.15	7.18	-70.9
	III	6.75	6.56	10.5	7.72	7.47	-103.9
	IV	7.15	6.89	10.8	7.51	7.66	-101.2
1991	I	6.91	6.63	11.0	7.49	7.56	-105.6
	II	7.56	7.27	10.7	7.98	8.14	-104.1
	III	7.35	7.22	8.5	8.32	8.17	-100.4
	IV	8.01	7.55	16.9	8.13	8.25	-82.9
1992	I	7.75	7.39	16.0	7.88	8.09	-86.5
	II	7.59	7.30	13.1	7.87	8.05	-110.2
	III	8.17	8.02	7.6	8.02	8.10	-80.2
	IV	8.41	8.13	11.4	7.91	8.22	-61.3
1993	I	8.62	8.29	14.2	8.28	8.60	-73.3
	II	8.51	8.18	12.8	8.15	8.34	-74.7
	III	9.00	8.79	10.9	8.46	8.60	-74.2
	IV	8.78	8.27	23.7	8.25	8.67	-82.1
1994	I	9.39	9.22	13.7	8.88	8.77	-28.9
	II	9.14	8.96	14.4	8.72	8.52	-32.2
	III	9.95	9.86	10.2	9.22	8.80	-49.4
	IV	9.99	9.86	9.5	9.02	8.73	-35.5

*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.*

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

(Continued)

		Women			Men		
		Returns to Schooling		Self-selection bias	Returns to Schooling		Self-selection bias
		Corrected	Uncorrected		Corrected	Uncorrected	
1995	I	9.87	9.45	23.6	9.21	8.94	-47.8
	II	10.20	9.91	19.6	9.57	9.45	-41.3
	III	9.40	9.28	13.4	9.19	9.09	-55.1
	IV	9.87	9.63	18.0	9.64	9.54	-52.9
1996	I	9.89	9.64	16.9	9.97	9.76	-47.9
	II	9.79	9.63	11.8	9.66	9.50	-38.8
	III	9.65	9.44	19.6	9.68	9.39	-56.7
	IV	9.97	9.78	12.6	9.97	9.71	-56.6
1997	I	10.00	9.86	15.6	9.96	9.65	-47.5
	II	10.10	9.92	15.4	10.10	9.79	-38.8
	III	9.79	9.68	14.7	9.81	9.22	-57.4
	IV	11.30	11.10	16.9	10.20	9.83	-54.2
1998	I	10.10	9.86	18.3	9.81	9.51	-40.0
	II	9.83	9.58	21.2	9.79	9.47	-47.9
	III	9.99	9.83	17.9	9.76	9.29	-50.5
	IV	10.20	9.97	17.8	9.77	9.52	-36.8
1999	I	9.91	9.75	12.9	9.57	9.11	-45.9
	II	10.10	9.85	14.8	9.94	9.45	-54.3
	III	9.82	9.73	7.2	10.00	9.54	-51.6
	IV	9.97	9.80	12.7	9.46	9.10	-51.9
2000	I	10.00	9.83	12.6	9.63	9.20	-55.3
	II	9.76	9.57	13.7	9.47	9.19	-40.7
	III	9.84	9.70	11.0	9.30	8.82	-50.7
	IV	10.00	9.93	7.3	9.43	9.19	-43.0
2001	I	9.67	9.54	10.7	9.50	9.27	-25.2
	II	9.51	9.35	11.5	9.31	9.14	-27.0
	III	9.71	9.59	9.6	9.36	9.04	-32.5
	IV	10.00	9.80	12.6	9.24	9.02	-27.4
2002	I	9.66	9.46	17.4	9.08	8.79	-40.9
	II	9.60	9.41	12.6	8.86	8.72	-21.2
	III	9.51	9.34	15.4	8.92	8.68	-24.8
	IV	9.10	8.94	11.2	8.95	8.81	-20.2

*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.*

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

		Women			Men		
		Returns to Schooling		Self-selection bias	Returns to Schooling		Self-selection bias
		Corrected	Uncorrected		Corrected	Uncorrected	
2003	I	9.64	9.47	11.0	8.73	8.58	-19.5
	II	9.99	9.77	13.9	9.10	8.92	-25.7
	III	9.82	9.67	16.8	8.47	8.07	-40.4
	IV	10.40	10.20	12.5	9.04	8.83	-23.6
2004	I	10.70	10.40	23.4	8.73	8.45	-33.4
	II	10.20	10.00	14.5	8.93	8.73	-26.9
	III	9.29	9.18	14.6	8.41	8.12	-26.6
	IV	9.19	9.01	11.2	7.90	7.76	-23.9
2005	I	6.92	6.85	5.6	7.74	7.52	-28.5
	II	7.28	7.21	4.6	7.88	7.64	-37.9
	III	9.26	9.15	10.5	8.47	8.27	-36.1
	IV	10.50	10.30	13.4	6.89	6.79	-33.4
2006	I	10.30	10.00	14.4	9.04	8.77	-42.4
	II	9.85	9.64	12.6	7.57	7.41	-44.4
	III	9.89	9.66	17.5	7.39	7.31	-23.3
	IV	9.28	9.15	8.9	7.45	7.39	-27.4
2007	I	10.10	10.00	7.7	8.67	8.42	-44.9
	II	9.59	9.28	21.9	7.99	7.89	-53.5
	III	9.41	9.29	11.1	8.28	8.00	-53.0
	IV	10.30	10.20	7.1	8.50	8.38	-50.3
2008	I	9.98	9.82	13.1	8.59	8.38	-39.4
	II	9.62	9.29	23.7	8.61	8.53	-45.1
	III	9.63	9.51	9.9	8.43	8.22	-50.1
	IV	10.40	10.20	13.7	7.24	7.23	-27.4
2009	I	8.41	8.36	3.9	8.00	7.83	-57.0
	II	10.30	10.20	4.5	7.71	7.59	-46.0
	III	9.49	9.35	12.7	8.62	8.34	-47.4
	IV	8.82	8.70	11.3	8.14	7.95	-37.9
2010	I	8.05	7.91	10.1	8.80	8.59	-38.7
	II	8.84	8.58	21.8	7.96	7.77	-46.3
	III	8.39	8.27	15.5	8.13	7.93	-43.8
	IV	8.33	8.10	20.4	8.18	8.00	-48.3

*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.*

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

(Continued)

		Women			Men		
		Returns to Schooling		Self-selection bias	Returns to Schooling		Self-selection bias
		Corrected	Uncorrected		Corrected	Uncorrected	
2011	I	10.30	10.00	15.2	7.66	7.37	-45.8
	II	7.43	7.44	-0.7	8.41	8.14	-46.4
	III	9.07	9.03	4.5	7.92	7.69	-42.3
	IV	9.44	9.28	11.2	7.25	7.15	-29.0
2012	I	9.67	9.57	8.5	7.95	7.85	-22.0
	II	9.35	9.26	8.9	8.07	7.89	-41.8
	III	9.18	9.08	10.9	8.11	7.93	-51.7
	IV	10.00	9.76	19.7	8.22	8.12	-48.4
2013	I	8.97	8.78	17.9	7.80	7.61	-40.1
	II	9.73	9.57	13.1	8.06	7.96	-46.6
	III	7.99	7.96	2.7	7.97	7.87	-28.7
	IV	8.77	8.65	8.9	7.91	7.80	-36.3
2014	I	8.94	8.91	2.4	7.73	7.59	-25.3
	II	7.69	7.50	14.2	7.69	7.54	-52.0
	III	8.26	8.21	4.2	7.59	7.46	-35.8
	IV	9.31	9.19	7.1	7.55	7.40	-41.1
2015	I	8.48	8.41	4.7	7.05	6.97	-17.6
	II	8.70	8.69	1.2	7.33	7.25	-16.0
	III	9.90	9.91	0.3	8.50	8.23	-36.7
	IV	8.33	8.23	10.3	6.13	6.04	-29.6
2016	I	10.20	10.00	16.0	7.77	7.44	-52.1
	II	10.90	10.80	8.1	8.04	7.85	-46.8
	III	8.54	8.35	14.5	8.49	8.36	-33.2
	IV	9.18	8.93	16.5	8.56	8.39	-34.0
2017	I	9.62	9.35	19.0	8.32	8.08	-40.5
	II	9.55	9.39	10.4	8.36	8.08	-41.3
	III	8.87	8.79	5.7	7.66	7.53	-23.9
	IV	9.26	9.07	13.3	7.48	7.22	-40.7
2018	I	8.57	8.48	6.0	7.81	7.52	-49.8
	II	9.51	9.27	13.8	6.05	5.90	-36.2
	III	9.43	9.36	7.8	6.48	6.36	-24.4
	IV	7.16	7.13	2.1	6.95	6.80	-35.6

*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 1% level.*

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

(Continued)

		Women			Men		
		Returns to Schooling		Self-selection bias	Returns to Schooling		Self-selection bias
		Corrected	Uncorrected		Corrected	Uncorrected	
2019	I	7.79	7.69	7.8	7.30	7.22	-18.0
	II	7.55	7.43	8.8	6.73	6.56	-32.3
	III	8.48	8.39	8.0	6.49	6.41	-20.6
	IV	9.16	8.92	17.0	6.11	6.08	-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.*

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

Tabla 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

*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.*

Tabla C.1. Gender wage gap decomposition

(Continued)

Year	Quarter	Gender wage gap (corrected)	Gender wage gap (uncorrected)	Endowment effect	Remuneration effect	Interaction effect	Self-selection bias
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

*Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU(1988-2000), ENE(2001-2004), ENOE(2005-2019). *Each of the presented coefficients is a percentage and is significant at the 5% level.*

Tabla C.1. Gender wage gap decomposition

(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

*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.*

Tabla C.1. Gender wage gap decomposition

(Continued)

Year	Quarter	Gender wage gap (corrected)	Gender wage gap (uncorrected)	Endowment effect	Remuneration effect	Interaction effect	Self-selection bias
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

*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.*

Tabla C.1. Gender wage gap decomposition

(Continued)

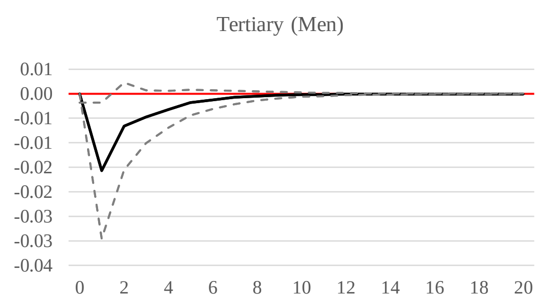
Year	Quarter	Gender wage gap (corrected)	Gender wage gap (uncorrected)	Endowment effect	Remuneration effect	Interaction effect	Self-selection bias
2019	I	25.7	8.4	-6.5	30.2	2.0	17.3
	II	22.1	6.7	-5.9	25.4	2.6	15.4
	III	25.7	8.6	-4.0	27.9	1.9	17.1
	IV	20.9	5.3	-6.7	24.4	3.2	15.6

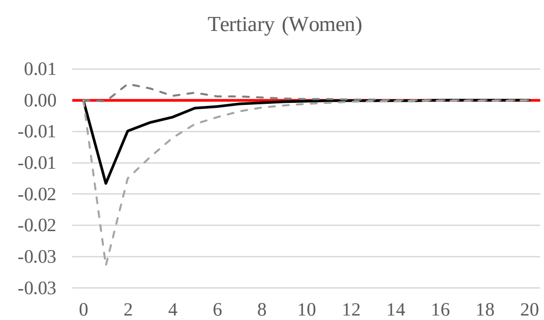
*Source: Own estimates with homologated databases of employment surveys in Mexico: ENEU(1988-2000), ENE(2001-2004), ENOE(2005-2019). *Each of the coefficients presented is a percentage and is significant at the 5% level.*

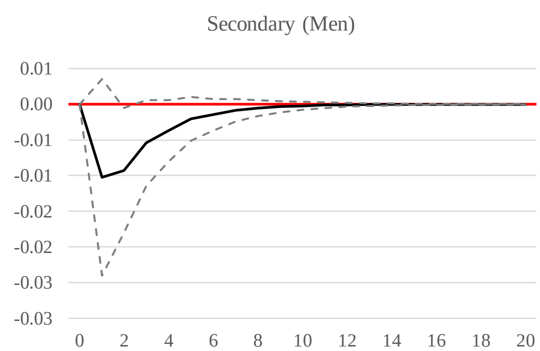
Figure A.2 VAR Models and Impulse-Response Function to negative shock in GDP
Time set: quarters after I-shock COVID-19 related to the economic crisis

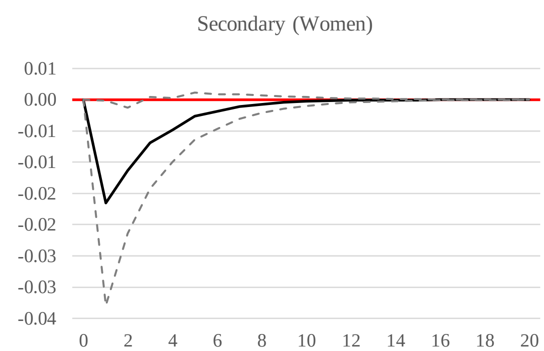
Model 1: Structure and dynamic of employment by economic sectors

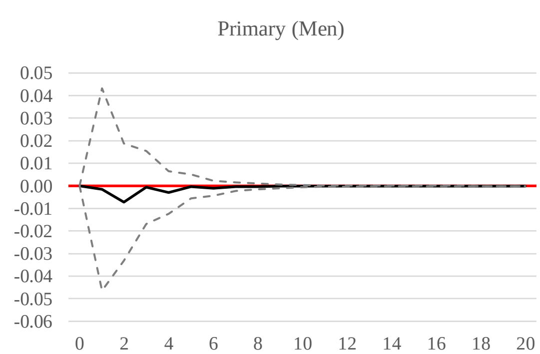
	Men			Women		
Variable	*Primary*	*Secondary*	*Tertiary*	*Primary*	*Secondary*	*Tertiary*
L1.eter.m	-0.605	-0.0189	-0.203	-0.542	0.0719	0.131
L1.eter.w	-0.122	-0.131	0.0614	-0.418	-0.214	-0.475 **
L1.esec.m	0.647	0.0209	0.393 **	-0.619	0.388 *	0.226
L1.esec.w	-0.259 ***	0.119	-0.231 *	0.510	-0.235	-0.0972
L1.epri.m	-0.332	-0.0454	-0.0344	0.0000576	-0.0202	-0.00258
L1.epri.w	-0.00446	-0.00554	0.00183	-0.467 ***	-0.00736	-0.00332
L1.gdp	0.129	0.261	0.369 *	-1.100	0.409 *	0.316 *
L1.whr.m	0.839	0.0717	0.186	2.123	0.215	0.257 *
L1.whr.w	-0.217	0.135	-0.0946	-1.268	0.0270	-0.157
Constant	-0.0211	-0.0106	-0.0126	0.0123	-0.0125	-0.00578
N	106	106	106	106	106	106
RMSE	0.123956	0.038329	0.038496	0.425477	0.045331	0.036048
Chi2(prob)	0.0016	0.1524	0.0314	0.0003	0.0533	0.0048

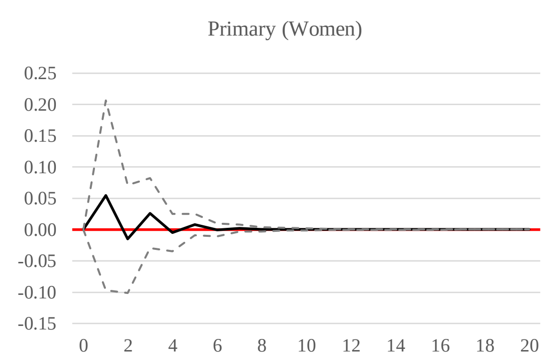












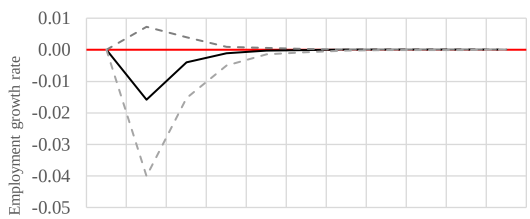
*p-value: 0.001***, 0.01**, 0.05*. Source: Own estimations with time series constructed and homologized of employment surveys (ENEU-ENE-ENOE). Seasonally adjusted series presented by growth rates.*

Figure A.3 VAR Models and Impulse-Response Function to negative shock in ITAEE
Time set: quarters after I-shock COVID-19 related to the economic crisis

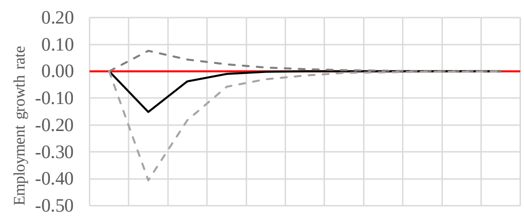
Model 1: Structure and dynamic of employment by skill levels in Nuevo Leon

Variable	Employment *Low-skilled* employment		*High-skilled* employment
L1.lsemp	-0.094		0.0603
L1.hsemp	0.135	*	0.0246
L1.itaee	0.480		0.416
L1.rwhr	-0.0335		-0.112
Constant	-0.0034		0.0094
N	131		131
RMSE	0.04913		0.064806
Chi2(prob)	0.1136		0.3503

Low-skilled



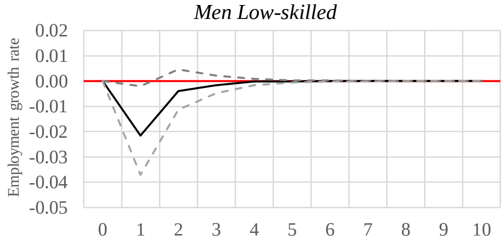
High-skilled



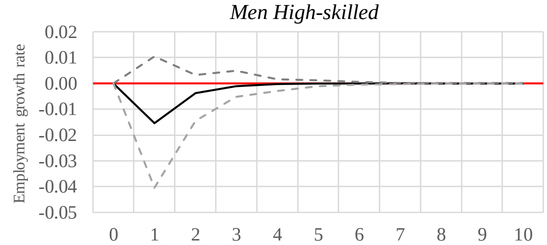
Model 2: structure and dynamic of employment by gender-skills in Nuevo Leon

Variable	Men *Low-skilled* employment		*High-skilled* employment	Women *Low-skilled* employment		*High-skilled* employment	
L1.lsemp.m	-0.176		0.0849	0.127		0.0666	
L1.lsemp.w	0.0822		-0.0191	-0.243	*	0.0107	
L1.hsemp.m	0.0862		-0.198	0.205		0.287	*
L1.hsemp.w	0.0536		0.125	-0.0519		-0.114	
L1.itaee	0.648	*	0.467	0.0468		0.294	
L1.rwhr	0.0121		-0.0524	-0.0707		-0.0159	
Constant	-0.00587		0.00687	0.00261		0.0144	
N	131		131	131		131	
RMSE	0.046642		0.068579	0.084761		0.089594	
Chi2(prob)	0.0591		0.3093	0.1276		0.4166	

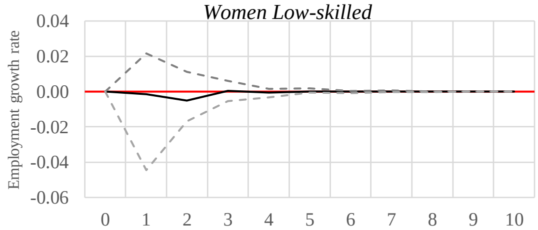
Men Low-skilled



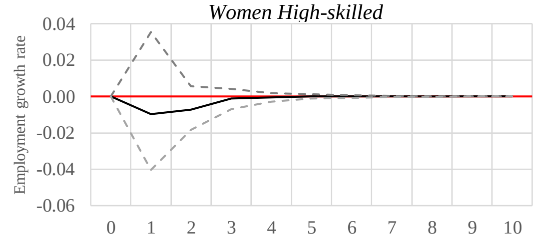
Men High-skilled



Women Low-skilled



Women High-skilled



*p-value: 0.001***, 0.01**, 0.05*.*

Source: Own estimations with time series constructed and homologized of employment surveys (ENEU-ENE-ENOE). Seasonally adjusted series presented by growth rates.