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Effects of Gender and Ethnicity on the Wage Gap Among Farmworkers in Northwestern Mexico

Efectos de género y etnicidad en la brecha salarial entre jornaleros agrícolas del noroeste mexicano

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ABSTRACT

The objective of this research is to analyze the effect of gender and ethnicity on the gender wage gap among farmworkers in the northwest region of Mexico, based on the 2020 census sample. By employing matching estimates and Inverse Probability Weighted Regression Adjustment (IPWRA) models, the effects on the mean and throughout the wage distribution of the sample are studied. It is observed that, in relation to gender and ethnicity, these are negative, especially when considered simultaneously, since among indigenous farmworkers, it is women who have the worst salaries. For women there are conditions of both a "sticky floor" and a "glass ceiling," and for men only the second. The results indicate that part of this difference can be interpreted as a result of discrimination.

Keywords: 1. farmworkers, 2. gender and race wage gap, 3. discrimination, 4. northwest region, 5. Mexico.

RESUMEN

El objetivo de esta investigación es analizar el efecto del género y la etnicidad en la brecha salarial entre jornaleros agrícolas de la región noroeste de México, con base en la muestra censal de 2020. Mediante estimaciones de pareamiento (matching) y modelos de probabilidad inversa ponderada ajustada por regresión (IPWRA), se estudian los efectos en la media y a lo largo de la distribución de los salarios de la muestra. Se observa que, en relación con el género y la etnicidad, estos son negativos, especialmente cuando se consideran de manera simultánea, ya que entre los trabajadores indígenas, son las mujeres quienes presentan los peores salarios. Para ellas se presentan condiciones tanto de "piso pegajoso" como de "techo de cristal", y para los hombres solo la segunda. Los resultados indican que parte de esta diferencia puede interpretarse como discriminación.

Palabras clave: 1. jornaleros agrícolas, 2. brecha salarial por género y etnicidad, 3. discriminación, 4. región noroeste, 5. México.

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INTRODUCTION

Agriculture is a relevant sector in the economy of many countries as it serves as a cornerstone for ensuring their food supply and security, while also contributing to job creation and various other benefits. The Mexican agricultural sector is characterized by its heterogeneity due to the coexistence of both subsistence producers and agro-industrial companies, as indicated by Yúnez Naude (2010). In this regard, based on the 2007 Agricultural Census (Inegi, 2012), Stabridis (2022) shows that, despite subsistence production units (with up to two hectares in size) accounting for half of the total, they only possess 5.5% of the total agricultural land, whereas the large units (over 20 hectares) possess 65% of productive lands. These larger units predominantly utilize irrigation water systems, employ the majority of the labor force, and cultivate crops through one or more cycles annually. Over time, they have developed agricultural practices that facilitate export to international markets through producer-exporter associations or under production contracts with transnational companies.

Based on the aforementioned points, we can categorize agriculture in Mexico into two primary types: the first revolves around the production of staple crops such as corn and beans, among others, which generally hold lower commercial value; and the second focuses on horticultural products (e.g., tomatoes, peppers, etc.) and fruit-bearing trees (berries,[3] cherries, nuts), which have a high commercial value. The labor demand patterns associated with these types of production ensure year-round, consistent export stream to regions like the United States, Europe, or Asia, resulting in substantial profits for these production units. This creates a heterogeneous demand for agricultural labor that depends on the type of production unit, whether commercial or subsistence. Regarding the latter, they typically rely solely on family labor; small commercial units tend to hire workers for short seasons; whereas large productive units that supply the domestic and export markets sustain a continuous demand for wage labor, which is fulfilled by agricultural laborers.

Farmworkers are (mostly) temporary workers who endure precarious[4] working conditions. Many of them are forced to migrate from their places of origin—usually from the poorest states—to the major agricultural regions located in the western and northwestern parts of Mexico in pursuit of improved wages. Precariousness characterizes the occupational landscape of agricultural laborers (Lara Flores, 2011). Notably, a significant portion of these laborers are indigenous individuals, of which between 10 and 15% are women, as evidenced in the data from the 2020 Population and Housing Census (Censo de Población y Vivienda 2020) and the National Survey of Household Income and Expenditure (Encuesta Nacional de Ingreso y Gasto de los Hogares [ENIGH]) (Inegi, 2020, 2021). The intersection of these variables reveals a wage gap in comparison to their counterparts, specifically non-indigenous individuals and men, respectively. While disparities in skill levels contribute to a portion of this wage gap, another significant part can be attributed to occupational segregation and discrimination.

[3] Berries, also referred to as 'soft fruit,' are a category of fruits that grow on bushes. They possess high protein and antioxidant content, making them agricultural products with the highest value per ton. This fruit category includes strawberries, raspberries, blueberries, and blackberries.

[4] They are characterized by the absence of contracts, low wages and job insecurity, among other factors.

The objective of this research is to analyze the impact of gender and ethnicity on the wage gap among farmworkers in the northwest region of Mexico, using the census sample data from the 2020 Population and Housing Census. Through the application of matching methods, we aim to uncover the direct influence of gender and ethnicity on the wage gap among agricultural laborers and determine whether this association can be attributed to discrimination. The advantage of employing this methodological approach is that it not only allows us to isolate the effects of gender and ethnicity on wages from other characteristics, but also facilitates the examination of the impact of additional variables such as age, education, and migration status. The study focuses on the northwest region of Mexico—encompassing Baja California, Baja California Sur, Sinaloa, and Sonora—due to its significance as a major agricultural area, characterized by high agricultural production value, substantial export levels, and a continuous demand for farmworkers throughout the year.

The results of the analysis reveal that women's wages tend to be 7% lower than those earned by men, and this difference increases between the middle and upper segments of the distribution. A similar trend is observed when considering the ethnicity variable, as indigenous individuals earn 17% less than non-indigenous individuals, and this gap becomes more pronounced in the upper segments of the distribution. In other words, the wage gap widens as it moves towards higher percentiles. When the gender and ethnicity variables are intersected, it becomes apparent that the lowest wages are earned by indigenous female farmworkers. It is considered that a portion of this disparity can be attributed to discrimination.

The article is divided into six sections: the first addresses the conceptual framework regarding farmworkers, the second considers the literature review on wage gaps, the third outlines the methodology used, the fourth describes the data source, the fifth presents the results, and in the final section, the conclusions are presented.

AGRICULTURAL DAY LABOR IN THE NORTHWEST REGION

Concept and Details

Various studies report widely different figures regarding the total number of farmworkers in the country. This not only occurs due to the diverse sources of origin but also, even when referring to the same source, there are studies that report different figures. This diversity of figures may be due to the different definition of farmworkers. For the purposes of this article, a farmworker is considered primarily a wage worker[5] whose occupation is agriculture.[6] In this sense, only those laborers who work in the agricultural sector are considered, excluding other categories and aligning with the postulations of Coubès (2018) and Stabridis and Salgado Viveros (2022).

The work of farmworkers is among the most precarious occupations due to low wages, limited access to social benefits compared to other wage-based occupations, and higher levels of labor

[5] Self-employed individuals, employers, and unpaid family workers were excluded.

[6] In this way, other day laborers in the primary sector such as livestock workers, forestry workers, and fishermen are excluded.

poverty (Stabridis & Salgado Viveros, 2022). When considering regional differences, it becomes evident that the working conditions of day laborers can be diverse. Some regions concentrate on the agro-export sector[7] and must adhere to social responsibility certifications imposed by the countries they export to. Consequently, these producers and exporting companies often provide better working conditions during the harvest season, which is when most workers provide their services. However, these improved working conditions are usually temporary and do not necessarily result in a reduction of their economic vulnerability.

To accommodate the diverse aspects of agricultural production, a categorization was devised, dividing the country into five distinct regions: 1) The southern-southeastern region, which includes the main states that export farmworkers: Chiapas, Oaxaca, Guerrero, and Veracruz, along with Campeche, Quintana Roo, Tabasco, and Yucatán. 2) The central region, comprising three states with significant agricultural production: State of Mexico, Morelos, and Puebla, as well as Hidalgo, Tlaxcala, and Mexico City. 3) The western region, the most important in terms of production volume and featuring states with a strong agro-export focus: Michoacán, Jalisco, and Guanajuato, along with other states with significant agricultural production such as San Luis Potosí, Nayarit, Zacatecas, Aguascalientes, Querétaro, and Colima. 4) The northeastern region, including the states of Chihuahua, Nuevo León, Durango, Coahuila, and Tamaulipas. 5) The northwestern region, encompassing the states of Sinaloa—the largest producer of tomatoes and peppers, among others—, Sonora—the leading producer of table grapes—, Baja California Sur and Baja California, states with an agro-export vocation, the latter being the one that, according to the 2020 Population and Housing Census,[8] has the municipality that reports the highest number of farmworkers in the country: San Quintín. This final region serves as the focus of this research.

There are two reasons for the decision to analyze the northwest region: firstly, the agricultural units concentrated in this region constitute one of the most productive areas; secondly, the intensification of its production generates a significant demand for day labor as indicated by Barrón Pérez (2000) and Grammont and Lara Flores (2004). These authors have elucidated the substantial flow of day labor demand experienced by the northwest region as an exporting hub, characterized by its migrant and multi-ethnic origins.

Table 1 displays agricultural production data by region for the year 2021. It is evident that despite comprising only 10% of the harvested area, the northwestern region generates 20.2% of the total agricultural production value. Notably, the agricultural production value per hectare in the northwestern region stands at 83 753 Mexican pesos (MXN), which is the highest among all regions. This figure is four times higher than that of the central and southern-southeastern regions, over twice as high as the northeastern region, and 50% higher than the central-western region. Similarly, based on the 2020 Population and Housing Census, the northwestern region offers the highest hourly wage for day laborers, nearly 42 MXN,[9] surpassing the 32 MXN paid in the northeastern and central-

[7] As is the case of the western and northwestern regions.

[8] This data was calculated from the microdata of the 2020 census sample (Inegi, 2021).

[9] This information is not included in the article but it can be requested from the authors.

western regions. In contrast, the southern-southeastern and central regions offer wages barely exceeding 20 Mexican pesos (Inegi, 2021).

Table 1. Area and Value of Agricultural Production by Region (2021)

Region	Planted area (ha)	Harvested area (ha)	Agricultural production value (millions of MXN)	Percentage of participation in agricultural production value	Average production value per hectare (MXN)
South-southeastern	5 108 794.8	4 932 383.1	114 981	16.6	23 311.4
Central	2 376 057.4	2 321 910.6	66 173.6	9.6	28 499.6
Central-western	5 709 845.4	5 458 629.9	275 904.4	39.8	50 544.6
Northeastern	3 265 219.7	2 847 052.7	95 930.8	13.8	33 694.8
Northwestern	1 691 117.6	1 669 640.3	139 838.8	20.2	83 753.9
Mexico	18 151 034.9	17 229 616.6	692 828.6	100	40 211.5

Source: Agricultural Production Data for 2021 obtained from the Agri-Food and Fisheries Information System (Sistema de Información Agroalimentaria y Pesquera SIAP).[10]

These data can explain why the northwestern region is the primary recipient of farmworkers and, as indicated by Grammont and Lara Flores (2004), why this region's workforce composition is predominantly indigenous and migrant. Despite this, farmworkers in the northwestern region constitute only 10% of the country's total day laborers. Table 2 illustrates that in the northwestern region, out of a total of 2.3 million farmworkers, only 237 395 are employed. Agricultural laborers make up 6.1% of the total wage workers, a figure that varies by region; in the northwestern region, they constitute 6.6% of the total wage workers.

Table 2. Total Agricultural Day Laborers by Region (2020)

Region	Agricultural laborers (male)	Agricultural laborers (female)	Total	Percentage of indigenous laborers	Percentage of the total wage workers
South-southeastern	751 110	45 777	796 887	43.2	11.3
Central	434 054	49 885	483 939	45.3	4.1
Central-western	578 706	88 596	667 302	21.6	7.3
Northeastern	102 135	8 273	110 408	11.1	1.9
Northwestern	181 951	55 444	237 395	33.4	6.6
Mexico	2 047 956	247 975	2 295 931	34.8	6.1

Source: Own elaboration based on the census sample of the 2020 Population and Housing Census (Inegi, 2021).

[10] This information is interactive and can be accessed at https://nube.siap.gob.mx/cierreagricola/

Regarding gender composition, it was found that 11% of farmworkers in the country are women, while in the northwestern region, they represent 23.4%. This finding supports the observations made by Lara Flores (1995) and Barrón Pérez (2000) regarding the systematic increase in female participation in wage agricultural labor since the 1990s. Lara Flores (1995) considers this increase as the beginning of the feminization of agricultural work, as the export-oriented agricultural sector emerged in the early 1990s. Escobar Latapí et al. (2019) demonstrated, through a survey conducted among farmworkers in agro-export companies in Jalisco, Michoacán, and Sinaloa, that over 40% of the workers are women. On the other hand, in the case of occupational structure in San Quintín, Baja California, Velasco et al. (2014), based on a representative survey of settlements in this municipality, found that women have a higher participation rate in horticulture compared to men.

Regarding ethnicity, the penultimate column of Table 2 shows that 34.8% of the workers identify as indigenous. The central and southern-southeastern regions surpass 40% of indigenous day laborers, while the northwestern region reports 33.4%. In the case of Sonora, Sariego Rodríguez (2007) distinguishes between two types of day laborers: the indigenous and the *mestizo*. The indigenous individuals, who are often temporary migrants, are typically engaged in the vegetable sector and face precarious working conditions. On the other hand, the *mestizo* workers are local to the region and primarily involved in table grape cultivation, experiencing relatively fewer challenges compared to their indigenous counterparts.

In the cases of Baja California and Baja California Sur, Velasco et al. (2014) and Velasco and Hernández (2018) examine ethnic occupational segregation in agriculture, as well as the precarious labor conditions experienced by indigenous farmworkers. Lara Flores (1998) describes a shift in agricultural activity from commercial agriculture to an agro-export model, accompanied by a process of labor flexibilization that has adversely impacted farmworkers' working conditions. In the case of San Quintín, Zlolniski (2019) found that despite some improvements in labor conditions, work intensification has been on the rise, negatively affecting farmworkers.

THE WAGE GAP

Previous Studies

The wage gap refers to the disparity in wages among workers in specific categories, such as gender, ethnicity, or migrant status. To establish the low-income nature of agricultural day labor, it is important to initially examine the wage disparity between farmworkers and other wage workers. To achieve this, the first column of Table 3 displays the wage for all wage workers by region. It's observed that the average hourly wage for all wage workers is 49.6 MXN. For agricultural laborers, it's an average of 27.4 MXN per hour, while for other wage workers, it's 51 MXN, representing a difference of 54%. Regional disparities in wages also exist, with the northwest region boasting the highest average of 42.8 MXN per hour. Similarly, the day laborer's wage is 30.9% less than that of non-day laborer wage workers.

When considering the gender wage gap, a slight difference is observed between men and women (29.4 vs. 27.2 MXN), with the central-western region having the smallest difference (1%) and the northeastern region having women earning more than men. Regarding the ethnicity wage gap, it's noted that indigenous farmworkers earn 19% less than their non-indigenous counterparts, with this difference being 1% in the northwestern region. This information compares only the average wages,[11] so in the methodology section, we will explain how much of this gap can be attributed to gender and ethnicity.

Table 3. Average Salary Per Hour, by Type of Worker and by Region (2020)*

Region	Total of laborers (MXN)	Non-agricultural laborer (MXN)	Agricultural laborer (MXN)
South-southeast	40.09	42.40	22
Central	50.69	51.99	20.56
Central-west	47.76	48.96	32.51
Northeast	54.72	55.14	32.10
Northwest	60.80	62.07	42.88
Mexico	49.59	51.04	27.39

* Expansion factors are used.

Source: Own elaboration based on the census sample of the 2020 Population and Housing Census (Inegi, 2021).

Wage gaps have been analyzed through their decomposition: One facet dissects the variances attributed to differences in human capital, while another aspect delves into wage structure disparities intertwined with discrimination. This analytical framework draws inspiration from seminal contributions by Oaxaca (1973) and Blinder (1973). Matching methods are employed to detect the effect of gender and ethnicity on wages through the control of observable characteristics. These methodologies build upon pioneering research by Ñopo (2008) and Frölich (2007), and they have been augmented by more recent investigations (Meara et al., 2020; Fisher et al., 2021) utilizing a multitreatment approach. The literature has evolved to encompass a broad spectrum, including comparisons between migrant and local workers, indigenous and non-indigenous individuals, among other dimensions. For ease of presentation, the literature review is divided into two sections: the first section dedicated to the dissection of wage gaps grounded in gender and ethnic-racial considerations, and the second section addressing wage decomposition among day laborers.

[11] It's important to note that detailed regional-level information is not presented because the statistical power of wages for day laborers in the 2020 census sample limits generalization at the regional level (Inegi, 2021).

The Wage Decomposition by Gender and Ethnicity

The article by Oaxaca (1973) stands as a pioneering work in the study of the gender wage gap. Employing an approach centered around estimating Ordinary Least Squares (OLS) regressions separately for each gender, the author decomposes the wage gap into two components: one attributing the gap to differences in characteristics between groups (work experience, education, etc.), and the other solely due to differences in wage structure, associated with discrimination. Due to its practicality, this method has found widespread application in numerous studies across the globe; however, certain limitations in its implementation have been acknowledged. Both the contributions of Oaxaca (1973) and Blinder (1973) laid the foundation for wage gap studies. Building upon this foundation, subsequent investigations have adopted more statistically robust methodologies, expanding the analysis of wage disparities to encompass other metrics such as quintiles or deciles (DiNardo et al., 1996; Machado & Mata, 2005; Firpo et al., 2009; Firpo et al., 2018). The gender wage gap has been studied by various authors: Ahmed and Maitra (2015) for Bangladesh; Biewen et al. (2020) for Germany; Zhang et al. (2008) for China; Pham and Reilly (2007) for Vietnam; Arabsheibani et al. (2018) for India; Arulampalam et al. (2007) for several European countries; and extensively documented for the United States by Blau and Kahn (2017).

In the work conducted by Ñopo (2008), the utilization of matching techniques to study the gender wage gap in Peru is proposed. He extends this analysis to encompass multiple Latin American countries (Ñopo, 2012). Similarly, Frölich (2007) employs the Propensity Score Matching (PSM) method to study the gap across the wage distribution in the United Kingdom. This methodology has been embraced by other researchers as well: Hirsch et al. (2013) studied the German context, Obermann et al. (2020) focused on Vietnam, and Morello and Anjolim (2021) delved into the Brazilian scenario. Furthermore, Meara et al. (2020) conduct a comprehensive study on the gender wage gap in the United States, exploring various matching techniques (including coarse,[12] Mahalanobis distance, and PSM), alongside a multitreatment approach. In this study, gender interacts with characteristics such as job type, union affiliation, among others, employing inverse probability-weighted regression adjustment models (IPWRA) to model average treatment effects (ATE).

Regarding the gender wage gap in Mexico, notable works include that of Alarcón and McKinley (1994), one of the earliest contributions on this topic, which employs the Blinder-Oaxaca decomposition (BOD); the authors found that a significant portion of the gender wage gap may be attributed to discrimination. For their part, Brown et al. (1999) study the gap considering occupational segregation; while in more recent studies like those by Popli (2013) and Arceo-Gómez and Campos-Vázquez (2014), the analysis of the gap goes beyond mean value, including quantiles as well. Furthermore, Arceo-Gómez and Campos-Vázquez (2014) build upon the decomposition proposed in DiNardo et al. (1996).

Turning to the wage gap based on ethnicity or race, the pioneering work of Blinder (1973) gains prominence as the first to analyze the disparity between white and black workers in the United States. Bucheli and Porzecanski (2011) conducted a similar examination for Uruguay, while

[12] Another matching technique; to learn more about this, it's suggested to refer to Iacus et al. (2012).

Gradín (2016) undertook a parallel study for Costa Rica. In both cases, the studies contend that a substantial portion of the gap can be attributed to discrimination. On the other hand, Neuman and Silber (1996) investigated the wage gap among Jewish individuals living in Israel, considering their country of origin as a possible marker of discrimination, and confirmed that the gap toward individuals born in Asia and Africa accounted for 26% of the total gap.

In the case of Mexico, numerous studies have delved into the gender wage gap; however, only a handful have directed their focus toward examining the indigenous wage gap among workers, and there is no work that explores the wage gap among farmworkers. Cano-Urbina and Mason (2016) find that there is a wage penalty for individuals who self-identify as indigenous, and this disparity intensifies when coupled with fluency in an indigenous language. Aguilar-Rodriguez et al. (2018) study the wage gap among bilingual indigenous workers (those who speak both Spanish and an indigenous language) and find that a significant portion of the difference is attributed to human capital, but there's an unexplained component associated with discrimination. Canedo (2019) explores the wage gap among indigenous workers using the Blinder-Oaxaca decomposition to analyze the entire distribution, and finds that a portion of the gap is largely explained by human capital, but the remainder is linked to discrimination, which is higher in the lower part of the distribution. Recently, Arceo-Gómez and Torres (2021) explored the indigenous wage gap and implemented a correction for indigenous identification bias using the 2018 National Household Income and Expenditure Survey (Encuesta Nacional de Ingreso y Gasto de los Hogares; ENIGH) (Inegi, 2019). The authors find that most of the gap is explained by selection bias, and the rest could be attributed, among other factors, to discrimination.

The Wage Decomposition for Farmworkers by Gender and Ethnicity

Despite the limited literature regarding the study of the wage gap among farmworkers, Fisher et al. (2021) analyze the gender wage gap and the benefit access gap among farmworkers in the United States, using BOD, Propensity Matching, and IPWRA models. Their study is based on data from the National Agricultural Workers Survey (NAWS), which has annual frequency and national representativeness. Their findings indicate that out of the 6% gender wage gap, the majority (80%) is attributed to discrimination and other unmeasured differences.

There are several studies on the gender wage gap in agriculture. Some of these studies focus specifically on the gender gap among agricultural producers. For instance, Fremstad and Paul (2020) conducted research on this topic in the United States; and regarding studies considering rural productivity aspects in African countries, we find Makate and Mutenje (2021) for Malawi, Ali et al. (2016) for Uganda, and Oseni et al. (2015) for Nigeria. Lastly, the work of Kilic et al. (2015) addresses the distributional aspects of the agricultural productivity gap in Malawi. Collectively, these studies showcase the enduring prevalence of gender-based discrimination. For the case of Mexico, only the study by Stabridis and Salgado Viveros (2022) estimates the gender wage gap among farmworkers, which is estimated at 15%. A portion of this gap is associated with

discrimination, although its measurement is only done for the average and utilizes the Blinder-Oaxaca decomposition method (BOD).

METHODOLOGY

As previously mentioned, the BOD serves as the initial approach to studying the wage gap. This model differentiates between the aspect defined by group composition differences and the component defined by wage structure, which is associated with discrimination. However, despite the method's practicality, it is considered to have several drawbacks. For instance, it only provides accurate estimations when parameter specifications are linear, as noted by Barsky et al. (2002). Similarly, Weichselbaumer and Winter-Ebmer (2005) argue that the unexplained component doesn't solely encompass discrimination but may also involve other omitted variables—such as productivity differences or occupational segregation—. In this regard, Ñopo (2008) points out that the BOD takes into account differences in worker distributions without considering that not all are necessarily comparable, potentially introducing biases in the estimations. To address this concern, the author employs exact matching techniques to analyze the wage gap among individuals with similar observable characteristics. Frölich (2007) also utilizes PSM to estimate the Average Treatment Effect on the Treated (ATT) related to gender differences in the wage gap.

For this article, matching techniques are applied to separately estimate the effect of gender and ethnicity on the wage gap among day laborers. For the simultaneous modeling of gender and ethnicity in the wage gap, IPWRA models are used. Each of these methods is briefly explained below.[13]

Single Treatment Matching

The objective of matching methods is to determine if there are statistically significant differences in a specific outcome variable between two comparable groups—one receiving the treatment and the other not receiving it (control group)—while considering the observable characteristics of both groups. In scenarios where treatment and control group assignments are random, any predetermined differences between the groups have a mean of zero. However, in cases where assignments are not random, predetermined differences (also known as selection bias) can exist, affecting the estimation of ATT. Matching methods use information about observable characteristics in both groups (e.g., being female or indigenous as the treatment variable)[14] to ensure that, through controlling these variables, estimates of ATT or ATE can be derived. Matching assumes that selection bias can be reduced by observable characteristics in both groups, such as the explanatory variables Xs in equation (1), which presents a probability model for treatment assignment. Matching relies on two

[13] To delve deeper into the topic, it is recommended to refer to Rosenbaum and Rubin (1983), Caliendo and Kopeinig (2008) and Cattaneo (2010).

[14] It is expressed in this manner so that the estimations reveal the effect of gender and ethnicity on the wage gap.

basic assumptions to eliminate selection bias. The first is the common support assumption, which requires that

$$0 < Pr\ [D = 1|\ X] < 1 \qquad (1)$$

In other words, for every value of each explanatory variable, it is necessary for both treated individuals and those from the control group to exist, whose probability of being selected with one or another characteristic is positive and less than one. This way, individuals with similar probabilities (one being in the control group and the other in the treatment group) are compared in their outcome variable, enabling the identification of the effect of being female or indigenous.

The second assumption requires that, when controlling for the vector of explanatory variables, participation in the treatment is independent of the outcome variables (in this case, the salary). This allows for an estimation of the treatment effect. This condition is known as the treatment *ignorability assumption*, which indicates that if there are unobservable variables that affect participation in the treatment, this assumption will not hold (Rosenbaum & Rubin, 1983). The ignorability assumption is also known as conditional independence.

In Propensity Score Matching (PSM), individuals are compared solely based on their probability of participating in the treatment. This approach condenses the information from an entire vector of variables into a single value (reducing dimensionality). The logic behind this methodology is that for individuals who share the same probability of treatment participation, their participation becomes random in the sense that it does not depend on the observable characteristics being used to derive the Propensity Score.

The steps to perform PSM are as follows:

1. Propose a specification to estimate a probability model (probit or logit) and obtain a selection probability (referred to as Propensity Score).
2. Arrange the data in ascending order based on the Propensity Score.
3. Divide the observations into strata in a way that there are no significant differences between the treatment and control groups within the strata (hypothesis tests for mean differences are conducted for this purpose).
4. Ensure that there are no significant differences in the variables that constitute the vector X between the treatment and control groups within the strata.

Once the Propensity Score has been estimated, the researcher should choose one of the estimation algorithms (nearest neighbor, Kernel, or radius) and then calculate the wage difference between the treated group (indigenous or women) and the control group (non-indigenous or men), and the difference obtained is attributable to gender or ethnicity. What the Mahalanobis distance does is take into account the distance between random variables in a multidimensional space and weight the covariance matrix of the variables to obtain probabilities similar to PSM.

To assess the performance of matching methods, it's important to verify that the paired strata of observations (treatments and controls) do not exhibit significant differences among them. Caliendo and Kopeinig (2008) suggest that if a bias of up to five percent is observed after matching,

it's a good indicator, and the same applies if explanatory variables do not show significance after matching.

Matching Estimates by Multitreatment

To consider the simultaneous impact of gender and ethnicity, the treatment effect models formulated by Cattaneo (2010) served as the foundation. In these models, an efficient estimator is proposed, consisting of two steps: the first step involves estimating the probability of each treatment category for all individuals (i.e., being non-indigenous male, non-indigenous female, indigenous male, and indigenous female). The second step entails estimating the treatment effect for each category through least squares regression, wherein the inverse of the estimated probabilities from the initial stage is employed as weighting factors. By generating probabilities for each group (observed and counterfactual),[15] it becomes possible to obtain the Average Treatment Effect (ATE). Another significant advantage of IPWRA models is their double robustness property, ensuring that if at least one of the models is correctly specified, the results will remain consistent. An important assumption of the IPWRA model is that the probabilities obtained for each individual in the sample must be positive. Moreover, the analysis extends beyond solely assessing the average wage distribution gap. It encompasses a comprehensive examination of the entire distribution, spanning from the 10th percentile to the 90th percentile.

Following Meara et al. (2020) and Fisher et al. (2021), the multi-treatment variable is defined as follows: 0=non-indigenous male; 1=non-indigenous female; 2=indigenous male; 3=indigenous female.

The effects will be compared, first with respect to the reference category (zero), and then between all categories.

INFORMATION SOURCES

The utilized database is the census sample derived from the extended questionnaire of the 2020 Population and Housing Census, which is representative of all municipalities and localities with more than 50 000 inhabitants—where representative samples were collected—. Similarly, data was collected through a census that included all households in municipalities characterized by a low Human Development Index, those with a high concentration of indigenous and/or Afro-descendant population, and those with fewer than 1 300 occupied households (Inegi, 2021). The census sample consists of approximately one-tenth of Mexico's households. From this sample, only farmworkers residing in the northwestern region were selected, considering the population aged 12 to 75 years in order to comprehensively capture the agricultural workforce. Therefore, the study subsample is constituted by the following variables:

[15] The counterfactual is the situation that did not happen to the individual. If someone receives a scholarship, the counterfactual is the situation where the person did not receive it. Since it's not possible to observe someone both with and without access to a program simultaneously, that's why groups were used.

- Indigenous: takes a value of one if the person identifies as indigenous and zero otherwise.
- Indigenous language: takes a value of one if the person speaks an indigenous language and zero if they do not speak any.
- Female: takes a value of one for females and zero for males.
- Age: in years.
- Education: years of schooling of the individual.
- Migrant: takes a value of one for those born in a different state than their current residence, and zero otherwise.
- Married/cohabiting: takes a value of one for individuals living in a partnership or cohabitation, and zero for those who are single.
- Extreme labor poverty: takes a value of one when the per capita income of the laborer's household is less than or equal to the minimum welfare line (established by the National Council for the Evaluation of Social Development Policy [Consejo Nacional de Evaluación de la Política de Desarrollo Social, Coneval]), and zero otherwise.
- Rural: takes a value of one for agricultural laborers living in localities with less than 2,500 inhabitants, and zero for those living in urban areas (with 2 500 inhabitants or more).
- ZLFN Municipality: takes a value of one for laborers living in municipalities within the Northern Border Free Zone (Zona Libre de la Frontera Norte; entire Baja California and the municipalities of Sonora, Chihuahua, Coahuila, Nuevo León, and Tamaulipas that border the United States), and zero otherwise.

The averages of these variables are shown in Table 4.[16] The average wage is 33.3 MXN per hour, being higher for men than for women (33.7 and 31.7 MXN, respectively). Similarly, non-indigenous day laborers earn more compared to indigenous ones (35.1 and 29.6 MXN, respectively). Notably, the gender wage gap is more pronounced among non-indigenous farmworkers (35.6 and 33.6 MXN for men and women, respectively) than among indigenous laborers (29.6 and 29.4 MXN for men and women, respectively), where it is nearly negligible. These findings offer valuable insights into the wage disparities rooted in both gender and ethnicity within the northwest region.

[16] An analysis was conducted, taking into account the complex design of the census sample. It was observed that the descriptive results with and without weighting were very similar, except for hourly wages for the groups. Therefore, the decision was made not to use the weighting. The authors express their gratitude to Dr. Enrique Minor (ITESM) for his comments on this aspect.

Table 4. Averages of the Sample of Farmworkers in the Northwest Region (2020)*

Variables	Total	Men	Women	Non-indigenous	Indigenous	Non-Indigenous Men	Non-Indigenous Women	Indigenous Men	Indigenous Women
Hourly wage (MXN)	33.29	33.76	31.73	35.1	29.57	35.59	33.29	29.65	29.36
Woman=1	0.23	-	-	0.21	0.28	-	-	-	-
Self-identified indigenous=1	0.33	0.31	0.4	-	-	-	-	-	-
Age in years	37.36	38.04	35.14	38.07	35.9	38.59	36.12	36.79	33.65
Years of schooling	6.97	7.02	6.81	7.22	6.47	7.22	7.23	6.58	6.18
Indigenous language speaker=1	0.14	0.12	0.19	0.01	0.4	0.01	0.01	0.38	0.46
Migrant=1	0.3	0.27	0.40	0.23	0.44	0.21	0.3	0.4	0.54
Married/cohabitating=1	0.61	0.62	0.57	0.6	0.61	0.61	0.57	0.62	0.58
Extreme labor poverty=1[1]	0.15	0.17	0.1	0.14	0.17	0.15	0.09	0.2	0.11
Lives in a rural location=1	0.41	0.45	0.3	0.44	0.35	0.47	0.31	0.38	0.28
Lives in municipality ZLFN=1[2]	0.13	0.12	0.14	0.14	0.11	0.13	0.15	0.1	0.13
Sample	20 298								

* Unweighted data.

[1] They are all individuals whose household per capita income is lower than the value of the food basket calculated by Coneval.

[2] The Northern Border Free Zone (Zona Libre de la Frontera Norte [ZLFN]) includes all the municipalities in Mexico that are bordering the United States; it also includes all the municipalities of Baja California.

Source: Own elaboration based on the census sample of the 2020 Population and Housing Census (Inegi, 2021).

Regarding the percentage of female farmworkers (23%), it is observed that this figure is higher among indigenous individuals (28%) compared to non-indigenous individuals (21%). One-third of the farmworkers (33%) self-identify as indigenous, with this proportion being higher among men (40%) than among women (31%). In terms of age, the sample's average is 37.4 years, with women (35.1 years) being younger than men (38 years). Similarly, indigenous individuals are younger (35.9 years) compared to non-indigenous individuals (38.1 years).

The average years of schooling are at the middle school level (7 years), demonstrating a very similar pattern between men and women. Additionally, non-indigenous individuals have 0.7 years more education compared to indigenous ones (7.2 and 6.5 years, respectively). This difference is smaller than the one observed when comparing workers without distinguishing their occupation. Indigenous language speakers constitute 14% of the total, with a notably higher percentage among workers who identify as indigenous (40%) than among non-indigenous individuals (1%). Approximately 30% of farmworkers in the northwest are migrants, which represents the highest percentage among all regions.

In the case of migrant farmworkers, the percentage of women (40%) exceeds that of men (27%). Similarly, the percentage of indigenous migrants (44%) is higher compared to non-indigenous migrants (23%). In all cases (total, men, women, indigenous, and non-indigenous), the farmworkers have a spouse. Regarding extreme labor poverty, it is observed that 15% of day laborers experience extreme poverty, with the rate being higher among men (both indigenous and non-indigenous) than among women. Approximately 40% of farmworkers reside in rural areas, defined as areas with fewer than 2 500 inhabitants. Day laborers in the northwest who live in a municipality of the *Zona Libre de la Frontera Norte* (ZLFN) constitute 13% of the total, with non-indigenous women workers having a slightly higher presence in ZLFN municipalities (15%).

RESULTS

The results of gender-based matching are shown in Table 5, where both the results obtained by PSM (Propensity Score Matching) and Mahalanobis matching[17] are presented. All the obtained results are significant at the 99% level, with the effect of being a woman on the average wage gap hovering around 4%. The results are expressed as a percentage of the gap and are in reference to the matched portion (matching).

Table 5. Gender Treatment Effects on the Wage Gap of Farmworkers in the Northwestern Region (2020)

Sample	Treatment =female	Control =man	Difference	Standard error	T-value	Treatment effect in the treated as a percentage of the gap
Matching by Mahalanobis Nearest neighbor						
Not matched	3.3024	3.3435	-0.0411	0.0085	4.83	-3.3
Matched	3.3024	3.3357	-0.0333***	0.0129	-2.57	
Calibration with a radius of 0.001						
Not matched	3.3024	3.3435	-0.0411	0.0085	-4.83	-4.2
Matched	3.2896	3.3326	-0.0431***	0.0110	-3.93	
Kernel (Epanechnikov)						
Not matched	3.3024	3.3435	-0.0411	0.0085	-4.83	-4.2
Matched	3.3003	3.3435	-0.0432***	0.0110	-3.92	
Propensity Score Matching Nearest neighbor						
Not matched	3.3024	3.3435	-0.0411	0.0085	-4.83	-4.3
Matched	3.3024	3.3459	-0.0435***	0.0135	-3.22	

(continues)

[17] A logistic regression model was estimated, yielding a common support region and a bias close to 1%. Due to space limitations, this information is not included in the article but can be requested from the authors. The same applies to the results of the ethnicity effect, as shown in Table 6. Standard errors were calculated using bootstrapping. The Stata command psmatch2 was employed.

(continuation)

Calibration with a radius of 0.001						
Not matched	3.3024	3.3435	-0.0411	0.0085	-4.83	-4.4
Matched	3.3025	3.3475	-0.0450***	0.0080	-5.64	
Kernel (Epanechnikov)						
Not matched	3.3024	3.3435	-0.0411	0.0085	-4.83	-4.3
Matched	3.3024	3.3464	-0.0440***	0.0084	-5.21	
Sample	20 298					

* Significant at 90%; ** significant at 95%; *** significant at 99%.

Estimation of Treatment Effect in the Treated for the Logarithm of Hourly Wage.

Standard errors by bootstrapping with 200 replications.

Source: Own elaboration based on the sample census of the 2020 Population and Housing Census (Inegi, 2021).

According to Meara et al. (2020), the treatment effect of being a woman on the wage gap is the difference between the matched groups. In other words, when comparing men and women with similar characteristics (age, education, etc.), it is observed that women receive 4% less in wages, which could be associated with discrimination and other unobservable characteristics such as productivity. In the occupation of agricultural laborers, it is difficult to see occupational segregation that does not favor women, as there is rather a segregation based on the type of production unit towards those that operate with more informal schemes, such as piece-rate payment.

Table 6 presents the results from ethnicity-based matching. The effect of ethnicity is significantly unfavorable for indigenous farmworkers, who receive a lower salary by 16% (ranging from 15.7% to 17.7% with Mahalanobis matching and 15.7% to 15.9% with PSM) compared to non-indigenous workers. This 16% divergence could be attributed to discrimination and, in some instances, is evident across various regions of the country where indigenous laborers are often assigned physically demanding tasks with limited opportunities for additional compensation. They might also prioritize working in informal production units that offer piece-rate payment without access to benefits. For the case of the United Kingdom, Meara et al. (2020) show that considering occupational segregation can yield slightly different results.

For the case of multi-treatment estimations, the results are presented in Table 7[18] based on Cattaneo (2010) and Cattaneo et al. (2013). When considering indigenous men as the reference category, the effects of the remaining categories on the wages of farmworkers are obtained.

[18] The results of the first stage are multinomial logit, but are not shown for space reasons.

Table 6. Ethnicity Treatment Effects on the Wage Gap of Farmworkers in the Northwest Region in 2020

Sample	Treatment =indigenous	Control =non-indigenous	Difference	Standard error	T-value	Treatment effect in the treated as a percentage of the gap
Matching by Mahalanobis Nearest neighbor						
Not matched	3.2216	3.3922	-0.1706	0.0075	-22.76	-17.7
Matched	3.2216	3.4160	-0.1944***	0.0289	-6.72	
Calibration with a radius of 0.001						
Not matched	3.3024	3.3922	-0.1706	0.0075	-22.76	-16.8
Matched	3.2896	3.3699	-0.1845***	0.0095	-19.33	
Kernel (Epanechnikov)						
Not matched	3.2216	3.3922	0.1706	0.0075	-22.76	-15.7
Matched	3.2216	3.3922	-0.1706***	0.0078	-21.89	
Propensity Score Matching Nearest neighbor						
Not matched	3.2216	3.3922	-0.1706	0.0075	-22.76	-15.9
Matched	3.2216	3.3943	-0.1727***	0.0341	-5.06	
Radius of 0.001						
Not matched	3.2216	3.3922	-0.1706	0.0075	-22.76	-15.6
Matched	3.2135	3.3836	-0.1701***	0.0212	-8.03	
Kernel (Epanechnikov)						
Not matched	3.2216	3.3922	0.1706	0.0075	-22.76	-15.7
Matched	3.2216	3.3922	-0.1706***	0.0202	-8.44	
Sample	20 298					

* Significant at 90%; ** significant at 95%; *** significant at 99%.

Estimation of Treatment Effect on the Treated for the Logarithm of Hourly Wage.

Standard errors by bootstrapping with 200 replications.

Source: Own elaboration based on the sample census of the 2020 Population and Housing Census (Inegi, 2021).

Table 7. IPWRA Model of Gender and Ethnicity Effects on the Wage Gap of Farmworkers in the Northwestern Region

Category	Mean	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Non-indigenous man	3.4060*** (0.0103)	2.9345*** (0.0163)	3.2005*** (0.0194)	3.3022*** (0.0116)	3.5899*** (0.0254)	3.9154*** (0.0192)
Non-indigenous woman	3.3315*** (0.0161)	2.925*** (0.0200)	3.1326*** (0.0317)	3.2222*** (0.0221)	3.4453*** (0.0095)	3.7612*** (0.0516)
Effect relative to non-indigenous male (%)	-7.5	-1.0	-6.8	-8.0	-14.5	-15.4
Indigenous man	3.2411*** (0.0081)	2.7114*** (0.0055)	2.9345*** (0.0096)	3.2020*** (0.0073)	3.4436*** (0.0111)	3.7186*** (0.0173)
Effect relative to non-indigenous male (%)	-16.5	-22.3	-26.6	-10.0	-14.6	-19.7
Indigenous woman	3.1648*** (0.0129)	2.7114*** (0.0170)	2.9221*** (0.0239)	3.1858*** (0.0195)	3.3557*** (0.0118)	3.5507*** (0.0335)
Effect relative to non-indigenous male (%)	-24.1	-22.3	-27.8	-11.6	-23.4	-36.5
Sample	20 298	20 298	20 298	20 298	20 298	20 298

* Significant at 90%; ** significant at 95%; *** significant at 99%.

Two-stage model with a first-stage multinomial probit.

Standard errors by bootstrapping with 3 000 replications.

Source: Own elaboration based on the census sample of the 2020 Population and Housing Census (Inegi, 2021).

The values of the logarithm of wages and the treatment effect are reported. In terms of the mean, it is observed that non-indigenous women earn 7.5% less than non-indigenous men, controlling for observable characteristics, so that 7.5% is the effect of being a non-indigenous woman. Indigenous men receive a salary 16.5% lower than that of non-indigenous men. The most disadvantaged category is that of indigenous women, as their salary is 24.1% lower than that of non-indigenous men, reflecting the vulnerability experienced by indigenous female laborers through their earnings.

Now it's worth questioning whether these gender and ethnicity effects persist throughout the wage distribution. This can be understood by examining the results by quantiles: at the 10th percentile, it is observed that the gender effect diminishes, with ethnicity playing a more significant role (among non-indigenous individuals, both men and women, the gender difference is only 1%). However the differences between non-indigenous men and indigenous men and women amount 22.2%.

As we move towards higher percentiles, the gender difference becomes more significant, and the ethnicity difference increases, becoming very high at the 90th percentile, where non-indigenous women earn 15% less than their male counterparts. The most extreme difference is observed among indigenous female laborers, whose salaries are 36.5% lower than those of non-indigenous men. This increase in the wage gaps at the higher percentiles indicates the presence of a glass ceiling,[19] as measured by Arulampalam et al. (2007). Table 8 provides a comprehensive comparison of all categories.

Table 8. Comparison of Effects by Categories of Farmworkers on the Wage Gap in the Northwest

Categories in comparison	Mean	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Non-indigenous woman vs. non-indigenous man	-0.0745*** (0.0192)	-0.0096 (0.0259)	-0.0680* (0.0372)	-0.0800*** (0.0251)	-0.1446*** (0.0271)	-0.1542*** (0.0552)
Indigenous man vs. non-indigenous man	-0.1650*** (0.013)	-0.2231*** (0.0173)	-0.2660*** (0.0215)	-0.1002*** (0.0137)	-0.1463*** (0.0280)	-0.1967*** (0.0258)
Indigenous woman vs. non-indigenous man	-0.2412*** (0.0164)	-0.2231*** (0.023)	-0.2784*** (0.0304)	-0.1164*** (0.0227)	-0.2342*** (0.0280)	-0.3646*** (0.0388)
Indigenous man vs. non-indigenous woman	-0.0904*** (0.0179)	-0.2136*** (0.0207)	-0.1981*** (0.0328)	-0.0202 (0.0232)	-0.0018 (0.0146)	-0.0426 (0.0547)
Indigenous woman vs. non-indigenous woman	-0.1667*** (0.0203)	-0.2136*** (0.0260)	-0.2105*** (0.0389)	-0.0364 (0.0291)	-0.0896*** (0.0149)	-0.2105*** (0.0611)
Indigenous woman vs. indigenous man	-0.0763*** (0.0153)	0.0000 (0.0180)	-0.0124 (0.0260)	-0.0162 (0.0207)	-0.0879*** (0.0162)	-0.1679*** (0.0375)
Sample	20 298	20 298	20 298	20 298	20 298	20 298

* Significant at 90%; ** significant at 95%; *** significant at 99%.

Marginal effects derived from the IPWRA Model in Table 7.

Standard errors by bootstrapping with 3000 replications.

Source: Own elaboration based on the census sample of the 2020 Population and Housing Census (Inegi, 2021).

When comparing indigenous men to non-indigenous women, it is observed that the former have a 9% lower salary than the latter on average. This difference is higher in the lower part of the distribution (19.8% at the 25th percentile). However, in the middle and upper parts of the distribution, the differences in wages between these groups are not significant. In the case of comparing women, the effect of ethnicity can be observed: non-indigenous women have a 16.7% higher salary than indigenous women on average, and when exploring this difference across the wage distribution, it widens at the distribution extremes and becomes insignificant at the median. At the 25th percentile, non-indigenous women have a 21.1% higher salary than their indigenous

[19] Glass ceiling refers to the phenomenon when the wage gap is wider at higher percentiles, and operationally, when the wage gap is higher at the 90th percentile compared to the 50th percentile (the median).

counterparts; similarly, this difference remains at 21.1% at the 90th percentile. This could be interpreted as the presence of a sticky floor[20] and glass ceiling.

The comparison between indigenous men and women allows us to observe the gender effect among indigenous individuals. On average, indigenous women tend to earn a salary 7.6% lower than their male counterparts, but when examining the difference across the wage distribution, it is observed that it only exists at the high end of the distribution, namely, a 16.8% difference at the 90th percentile.

The significance of these results lies in the interaction between gender and ethnicity effects on wages, which can vary depending on the part of the distribution being examined. Thus, it is demonstrated that the gender-ethnicity interaction (indigenous women) indicates a substantial difference ranging from 21 to 36%. This difference is only diminished at the median of the distribution. In this manner, both effects contribute to the widening of disparities.

To corroborate the robustness of the results obtained with the IPWRA model, we conducted a comparison with the estimates of gender and ethnicity gaps using the RIF decomposition methods (Firpo et al., 2018), using the commands developed by Rios-Avila (2020). The results presented in Tables 9 and 10 show that the gender and ethnicity gaps favor male and indigenous workers. It is observed that most of the gap remains unexplained by the characteristics of the groups, which does not necessarily imply that this is due to discrimination but, as noted by Meara et al. (2020), reflects the high degree of heterogeneity among the groups, something that is evident from Table 4, where differences in age, education, and migration status are evident. Therefore, it is considered that the results obtained with the matching and IPWRA models are a more suitable approach for modeling the studied effects compared to the RIF models.

Table 9. Oaxaca-RIF Decomposition of the Ethnicity Wage Gap in Farmworkers (2020)

Differential	Mean	25th percentile	Median	75th percentile
Non-indigenous	3.3922***	3.2231***	3.3197***	3.5386***
	(0.0043)	(0.0015)	(0.0043)	(0.0065)
Indigenous	3.2216***	2.9703***	3.2560***	3.4320***
	(0.0061)	(0.0064)	(0.0029)	(0.0053)
Total ethnic gap	0.1706***	0.2528***	0.0636***	0.1066***
	(0.0075)	(0.0066)	(0.0051)	(0.0083)
Gap decomposition				
Explained	0.0267***	0.0017	0.0154***	0.0475***
	(0.0035)	(0.0011)	(0.0033)	(0.0048)

(continues)

[20] This occurs when the gap is larger at the lower end of the distribution.

(continuation)

Percentage of total	15.7	0.7	24.2	44.6
Unexplained	0.1439***	0.2511***	0.0482***	0.0590***
	(0.0075)	(0.0065)	(0.0057)	(0.0091)
Percentage of total	84.3	99.3	75.8	55.3
Sample	20 298	20 298	20 298	20 298

* Significant at 90%; ** significant at 95%; *** significant at 99%.
Standard errors in parentheses.
RIF-OLS regression estimates.

Source: Own elaboration based on the census sample of the 2020 Population and Housing Census (Inegi, 2021).

Table 10. Oaxaca-RIF Decomposition of the Gender Wage Gap in Farmworkers (2020)

Differential	Mean	25th percentile	Median	75th percentile
Men	3.3467***	3.0854***	3.2632***	3.5242***
	(0.0041)	(0.0051)	(0.0025)	(0.0047)
Women	3.3020***	3.0731***	3.3088***	3.4715***
	(0.0071)	(0.0083)	(0.0032)	(0.0055)
Total ethnic gap	0.0447***	0.0123	-0.0456***	0.0527***
	(0.0082)	(0.0097)	(0.0041)	(0.0073)
Gap decomposition				
Explained	-0.0319***	-0.0420***	-0.0202***	-0.0168***
	(0.0037)	(0.0042)	(0.0020)	(0.0035)
Percentage of total	71.4	-341.5	-44.3	-31.9
Unexplained	0.0766***	0.0543***	-0.0254***	0.0695***
	(0.0080)	(0.0095)	(0.0041)	(0.0075)
Percentage of total	84.3	441.5	55.7	131.9
Sample	20 298	20 298	20 298	20 298

* Significant at 90%; ** Significant at 95%; *** Significant at 99%.
Standard errors in parentheses.
RIF-OLS regression estimates.

Source: Own elaboration based on the census sample of the 2020 Population and Housing Census (Inegi, 2021).

CONCLUSIONS

The objective of this article was to analyze the effect of gender and ethnicity on the wage gap among farmworkers in the northwest of Mexico, both on the mean and across the wage distribution, to determine if there is a component of discrimination. These effects were found using matching methods, considering gender or ethnicity as the treatment, and then, with the use of IPWRA models, to simultaneously evaluate both effects.

The results obtained through matching reveal a direct negative effect of both gender and ethnicity on wages, indicating that in an environment where farmworkers with similar observable characteristics are compared, women tend to have lower wages than men, and indigenous individuals have lower wages than non-indigenous individuals. The effect of ethnicity is greater than that of gender (16.5% vs. 4%). One advantage of matching estimates over the BOD approach is its ability to control for heterogeneity, thereby significantly reducing selection bias in observable characteristics.

To assess the simultaneous effect of gender and ethnicity across the wage distribution, IPWRA models were employed. The results in the mean indicate that non-indigenous men earn the highest wages, whereas indigenous workers, both men and women, have the lowest wages.

When these gaps were analyzed across the wage distribution, it was observed that in the lower part of the distribution, only the effect of ethnicity was significant, with the gender effect not being significant. However, as we moved towards higher percentiles, the effect of ethnicity decreased slightly while the gender effect increased. This is why non-indigenous women earn almost the same wages as their male counterparts at the 10th percentile, but much higher than indigenous individuals. However, at the 90th percentile, non-indigenous women earned wages 15% lower than non-indigenous male laborers, and the gap between indigenous workers and non-indigenous men increased, signifying the presence of a gender-related glass ceiling. In the case of indigenous men compared to non-indigenous men, the effect of ethnicity decreased as we moved along the distribution. When comparing the effect of ethnicity in women, it was observed that the gap was larger at the extremes, with no discernible wage differences at the median. This dual pattern suggests the simultaneous existence of both a sticky floor and a glass ceiling.

Lastly, when comparing the gender effect among indigenous laborers, it was observed that wage differences between indigenous men and women were not significant from the 10th percentile to the median of the distribution. However, in the upper part of the distribution, lower wages for women became apparent, indicating the presence of a glass ceiling. As mentioned earlier, there is limited research on the wage gap among farmworkers. For instance, in the United States, Fisher et al. (2021) found that women earned 6% less than men, partly due to discrimination. In Mexico, Stabridis and Salgado Viveros (2022) discovered that female laborers earned 15% less than their male counterparts, with a portion of this difference attributed to discrimination.

The negative effects observed in wages concerning gender and ethnicity cannot be solely attributed to factors like discrimination. There are also unobservable characteristics at play, such as the type of payment (e.g., integrated salary, mixed, piece-rate), potential occupational selection

(certain tasks may be assigned to women or indigenous individuals, or they may choose them for higher pay), or gender-related challenges that women might face in accessing extra payments for longer working hours, potentially resulting in lower wages. However, it is possible to attribute these negative effects, at least to some extent, to gender and ethnicity discrimination.

It is worth highlighting that in future research, it would be valuable to include gender-specific labor supply at the local level as a variable that may affect wages, as well as incorporating information about producers that could have an effect on wages or influence labor supply. The current challenge stems from the lack of a comprehensive survey or census that captures the specific characteristics of agricultural laborers or the productive units they work for, similar to what is collected in the United States with the National Agricultural Workers Survey (NAWS) or similar agricultural surveys in Chile, Peru, and Colombia. The National Agricultural Survey (Encuesta Nacional Agropecuaria) conducted by Inegi offers limited information, and its accessibility is restricted.

Translation: Erika Morales.

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