
RESEARCH ARTICLE

Labor Market Discrimination Against Indigenous Peoples in Mexico: A Decomposition Analysis of Wage Differentials

Ana Canedo

Mexico's indigenous peoples are amongst the country's most vulnerable and marginalized. According to the Mexican National Council for the Evaluation of Social Development Policy, the percentage of indigenous peoples who live in poverty in Mexico is nearly double that of the general population: 70.3 percent versus 38.6 percent, respectively. In this context, the present study aims to explore why the gap between the indigenous and non-indigenous populations is not closing, even after occupational differences and the rural-urban divide are taken into consideration. This paper employs Oaxaca-Blinder (OB) decomposition techniques as well as two quantile decomposition approaches with data from the 2016 National Household Expenditure Revenue Survey (ENIGH) to analyze wage differentials along the entire wage distribution and differences in the prevalence of informal employment among indigenous and non-indigenous peoples in Mexico. Understanding the underlying causes of these disparities is crucial for the design of sustainable policies that may help reduce the gap in the living conditions of indigenous and non-indigenous peoples. Findings confirm that differences in coefficients account for a significant proportion of the gap in indigenous earnings, indicating that indigenous disadvantage would persist even if human capital outcomes and access to formal employment were to improve for this population subgroup.

Keywords: Indigenous wage inequality; Labor market discrimination; Mexico; Wage decomposition; Quantile decomposition

1. Introduction

Mexico's indigenous peoples are amongst the country's most vulnerable and marginalized. While they account for only 9 percent of the total population, they are over-represented among the poor. According to the Mexican National Council for the Evaluation of Social Development Policy (or CONEVAL, its acronym in Spanish), the percentage of indigenous peoples who live in poverty is nearly double that of the general population: the rates were 70.3 percent versus 38.6 percent in 2016 (CONEVAL 2016). This disparity in the prevalence of poverty raises the following questions. Why are ethnic wage inequalities so pronounced in Mexico? Where are the pay differences between indigenous and non-indigenous peoples most present? If differences in human capital characteristics such as education and work experience were removed, would they still fare worse than their non-indigenous counterparts? If so, what kinds of policies could help bridge the present gap?

The concentration of poverty among indigenous populations is increasingly being recognized in the development literature (Garcia-Aracil and Winter 2006;

Liberato et al. 2006; Ñopo 2012; Psacharopoulos and Patrinos 1994; Sandefur and Pahari 1989; Wilson and David Macdonald 2010). Scholarly research in Latin America has revealed that indigenous peoples report lower labor market earnings and experience higher levels of poverty. Psacharopoulos and Patrinos (1994) were the first to explore differences in ethnic groups' living conditions among Latin American countries, finding a significant gap between the living conditions of indigenous peoples and those of non-indigenous peoples, as well as a positive correlation between being indigenous and living in poverty.

Castaneda-Navarrete (2013) contributed to the advancement of the still incipient literature on the study of poverty from an ethnic perspective in Mexico by using the Mexican Family Life Survey (MxFLS) to analyze differences in poverty dynamics between indigenous and non-indigenous peoples. Her results indicate that indigenous peoples face greater difficulties than non-indigenous people in escaping poverty, particularly due to their socio-economic disadvantages like lower schooling levels, lack of adequate infrastructure, labor discrimination, and vulnerability to natural disasters (Castaneda-Navarrete 2013). In a comparative study among Latin-American countries, Hall and Patrinos (2004) found that the share of Mexico's

indigenous peoples living in poverty had remained unchanged, despite significant reductions in national poverty rates from 1994 to 2004. This pattern suggests that indigenous and non-indigenous peoples are not benefiting equally from Mexico's economic growth and the country's major social and poverty reduction programs (Hall and Patrinos 2004). Following Hall and Patrinos (2004), González de Alba (2010) and García-Moreno and Patrinos (2011) found further evidence of a significant indigenous earnings gap in Mexico (González de Alba 2010; Moreno, Patrinos, & Anthony 2011).

While most empirical studies confirm that a great share of the gap can be explained by indigenous peoples' lack of representation in high-paid occupations, the empirical literature in Mexico suggests that indigenous discrimination also plays an important role. However, thorough search of the literature revealed that most of these studies focus on investigating the gap in mean wages, overlooking difference with respect to the wage distribution and the factors affecting the magnitude of the gap. In this context, the present study contributes to the literature of indigenous discrimination in the Mexican labor market in several ways. First and foremost, the study uses quantile decomposition techniques to analyze ethnic wage differentials in Mexico along the wage distribution. Second, this study examines the gap in participation in the formal labor market in addition to decomposing wage inequalities. Finally, the study employs 2016 wage data and places particular focus on analyzing whether there is an increased wage-penalty for indigenous women in the Mexican labor market. These approaches are relevant for policy purposes given that the findings can provide deeper insights into the nature of income differentials, allowing us to identify where the ethnic wage gap is more pronounced and why it is not closing. Understanding the underlying causes of these disparities is crucial to the design of effective public policies that may help reduce the gap in living conditions between indigenous and non-indigenous peoples in Mexico.

2. The Literature on the Indigenous Wage Gap in Mexico

Despite increasing levels of labor force participation and some advancements with regards to labor regulations that promote equality and non-discrimination, indigenous workers in Mexico continue to earn significantly lower wages than their non-indigenous peers (Delaunay 2005; Moreno et al. 2011). On average, Mexico's indigenous peoples earn 45.5 percent less than the non-indigenous population (see **Figure 1**). At the same time, indigenous peoples are overrepresented in the Mexican informal economy. According to CONEVAL's estimates, eight out of ten indigenous Mexicans have informal jobs (CONEVAL 2016). While labor market barriers such as indigenous peoples' low educational indicators and occupational preferences explain an important part of this pay and "formality" gap, empirical findings also suggest that there is a penalty for being indigenous in the Mexican labor market.

Using the 1997 *Encuesta Nacional de Empleo en Zonas Indígenas*, Hisamatsu and Ukeda (2002) showed that self-identifying as indigenous—which is indicated by speaking an indigenous language—is associated with earning lower wages than in the non-indigenous population. Such disparities persist even after controlling for income-related variables such as education, work experience, geographic location and land assets (Hisamatsu and Ukeda 2002). Similar results are presented in McNeilly's (2013) dissertation work. The author employs data from the 2010 National Household Expenditure Revenue Survey (ENIGH, by its acronym in Spanish) to conduct a traditional OB decomposition analysis of ethnic income differentials in Mexico, finding that differences in endowments could not entirely account for this gap (McNeilly 2013).

More recently, Aguilar-Rodríguez et al. (2018) used the decomposition method of Oaxaca and Choe (2016) to analyze the wage gap between indigenous language monolinguals and Spanish-indigenous-language bilinguals in Mexico, using a subsample of the Mexican Census from the 2000–2010 period. The authors found evidence of a

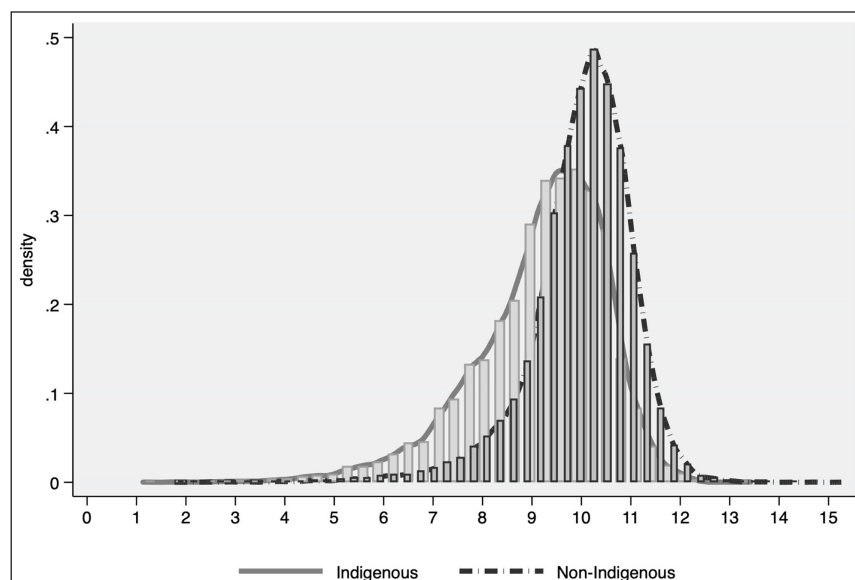


Figure 1: Distribution of the Logarithm of Monthly Wage by Ethnicity.
Source: Author's calculations based on the ENIGH 2016.

positive return to bilingualism among indigenous peoples. Furthermore, the authors reported that only 60 percent of the wage gap can be explained by differences in observable characteristics, such as years of education and work experience, factors traditionally used to explain wage disparities (Aguilar-Rodriguez et al. 2018). Cano-Urbina and Mason (2016) further explored the labor market penalty associated with being indigenous by analyzing data from both the Mexican Census and the Mexican Family Life Survey (MxFLS). Their findings confirm that the indigenous pay gap cannot be entirely explained by differences in human capital characteristics, even after controlling for the individual's education, cognitive ability, and fluency in Spanish. Additionally, they found that this ethnic labor market disadvantage is particularly pronounced in smaller cities and among self-employed workers (Cano-Urbina and Mason 2016).

There appears to be a consensus in the empirical literature that there is more informing the ethnic wage gap in Mexico than potential differences in observable human capital, occupation, and demographic characteristics. Labor market and welfare differences among indigenous and non-indigenous peoples can be mainly attributed to the spatial segregation of indigenous communities. The vast majority of Mexico's indigenous peoples live in small communities—most of which are located in the poorer southern and southeastern states. Many of these remotely located areas lack basic infrastructure such as roads, sewage, and electricity systems; this isolation prevents indigenous peoples from attaining higher levels of education, receiving health care and social security, accessing credit from financial institutions for self-employment, and from obtaining well-paid jobs. In addition, the poor quality of education in those communities—due to the lack of teachers and adequate spaces for learning—affects the returns on schooling for indigenous peoples (OECD 2017).

Another well-explored factor contributing to this pattern of lower wages and marginalization among ethnic minorities is that indigenous workers, on average, demonstrate fewer desirable human capital characteristics, like knowledge, skills, and professional experience. Parker et al. (2002) showed that, in Mexico, even within highly-marginalized rural areas, indigenous children on average fare worse in educational outcomes (years of schooling and educational performance) than non-indigenous children (Parker et al. 2002). These disparities in education carry into adulthood occupational outcomes, as indigenous peoples' low levels of education consequently prevent them from entering higher-paying skilled jobs. To date, the illiteracy rate for indigenous peoples remains significantly higher than the national average (27.2 percent compared to 5.4 percent) (OECD 2017).

An additional reason for the ethnic gap in labor earnings could be due to Mexico's informal employment sector. Often, the livelihoods of indigenous peoples depend on traditional occupations, such as farming, hunting or fishing, and craft production. Such activities rarely occur within the Mexican formal economy (Lunde et al. 2007). Moreover, when looking for paid work, indigenous peoples are often confined to jobs in the informal economy (domestic work, street vending, construction, and agriculture, among others). Thus, indigenous peoples are overrepresented in the

informal sector, remaining outside the reach of established labor laws and hence they earn lower wages.

Finally, the gap between indigenous and non-indigenous populations could also be explained by an unobservable indirect effect such as labor-market discrimination (Oaxaca and Ransom 1994). In the context of the indigenous wage gap, it could be that while human capital characteristics and informality ($\mathbb{X}$) influence individuals' wages ($\mathbb{Y}$), a part of these effects can be ascribed to an indirect and unobservable influence such as labor-market discrimination ($\mathbb{Z}$): indigenous peoples may face discrimination when looking for a job, which in turn affects their work experience and skills, making them less likely to find higher-paying employment. This situation necessitates decomposition techniques to measure whether unobservable indirect effects can explain part of the ethnic wage gap in Mexico, once differences in observable demographic, human capital, and occupational characteristics (endowments) have been accounted for.

3. Data and Methods

Data and Descriptive Statistics

This study analyzes data from the 2016 National Household Expenditure Revenue Survey (ENIGH), the leading household survey of Mexico's National Institute of Statistics and Informatics (INEGI). The ENIGH data is well-suited for this study for several reasons. First, the ENIGH is a nationally representative survey of Mexican households, containing detailed information about the household's characteristics, its income and expenditures, and the demographics of its members. Second, the ENIGH is the official source of data for income inequality and poverty measurements; it is the same data source CONEVAL uses for the Mexican official poverty measurement (MPM). Third, since its 2008 edition, the ENIGH has included a question about indigenous language, allowing for identification of the indigenous population according to the definition provided by the National Commission for the Development of Indigenous People (or CDI, its acronym in Spanish), in which a person is considered indigenous if he/she declares speaking an indigenous tongue (CONEVAL 2010; Navarrete Linares 2008).

Since this study seeks to understand the underlying factors associated with the indigenous wage gap in Mexico, the analysis centers exclusively on the employed population who reported earning a wage. In addition, the sample is restricted to individuals aged 15 to 65 years—to capture the working age population in Mexico (OECD 2016). The 2016 ENIGH sub-dataset utilized in this study consists of socio-economic and demographical variables for 130,051 observations.

Table 1 presents the descriptive statistics by ethnicity. The summary statistics indicate large differences between indigenous and non-indigenous peoples' average wages. Indigenous peoples exhibit higher average years of work experience and work fewer hours a week. Furthermore, there are substantial compositional differences in the years of schooling and in the proportion of people living in rural areas between both population subgroups. There are also significant differences in terms of occupational sectors (see Figures A1 and A2 in the appendix for more descriptive statistics).

Table 1: Descriptive Statistics by Ethnicity, 2016.

Variable	Non-indigenous (n = 118,744)		Indigenous (n = 11,307)	
Individual's characteristics	Mean	Std. Dev	Mean	Std. Dev
Wage	34,261	45,137.13	18,668	22,930.52
Age	38.41	14.64	41.54	16.21
Years of schooling	10.10	4.26	6.98	3.98
Years of experience	28.31	16.32	34.56	18.17
Hours worked	42.62	20.2	38.21	21.16
	Percentage		Percentage	
Female	39.77		39.09	
Locality Size				
Population of fewer than 2,500	35.53		64.78	
Between 2,500–14,999 inhabitants	13.55		18.84	
Between 15,000–99,999 inhabitants	13.45		7.81	
Population of more than 100,000	37.48		8.57	

Source: Author's calculations based on the ENIGH 2016.

The Oaxaca-Blinder Decomposition

The Oaxaca-Blinder (OB) decomposition is a regression decomposition method that allows us to break down the factors associated with the mean labor income gap between two populations (Blinder 1973; Oaxaca 1973). Thus, in the context of the Mexican ethnic wage gap, the model evaluates what would happen if indigenous peoples were to have the same human capital characteristics as non-indigenous peoples, to assess whether there are significant group differences in unobserved predictors that indicate that indigenous peoples experience discrimination and are more vulnerable to informality. This technique decomposes differences in mean outcomes between two groups: the differences in endowments or observable characteristics ($\mathbb{E}$) and the differences in coefficients or unobservable effects ($\mathbb{C}$). In this way, it analyzes differences that can be explained through the endowments of income-generating characteristics and those that cannot (Fortin et al. 2011; Oaxaca and Ransom 1994). Additionally, this technique allows us to further identify what part of the differential is attributable to human capital endowments or observable characteristics ($\mathbb{E}$), what part is due to differences in unobservable effects ($\mathbb{C}$), and what is the interaction term between the differences in coefficients and differences in endowments ($\mathbb{CE}$). Thus, the mean difference in $\mathbb{Y}$ (log-wages) between groups $\mathbb{I}$ (indigenous) and $\mathbb{NI}$ (non-indigenous) can be decomposed as follows:

$$\bar{Y}_I - \bar{Y}_{NI} = \underbrace{(\bar{X}_I - \bar{X}_{NI})\beta_{NI}}_{\mathbb{E}} + \underbrace{\bar{X}_{NI}(\beta_I - \beta_{NI})}_{\mathbb{C}} + \underbrace{(\bar{X}_I - \bar{X}_{NI})(\beta_I - \beta_{NI})}_{\mathbb{CE}} + \bar{e}_I - \bar{e}_{NI}$$

Although the OB decomposition technique is widely used to analyze ethnic disparities in labor market contexts, this approach presents several limitations (Fortin et al. 2011). First, the relationship between the observable characteris-

tics or the endowments and wages is assumed to be linear, which might not be the case. Second, and most importantly, it focuses only on the average wage gap decomposition between the two population subgroups without considering heterogeneous effects between the endowments and the wages across the distribution of the ethnic wage gap. This last point is particularly important because returns to education and work experience are known to vary across the income distribution.

Consequently, to better understand the ethnic wage gap in Mexico, the second part of the analysis employs quantile regression decomposition techniques (Melly 2007, 2006; Firpo et al. 2009). As with the OB decomposition, these methods allow for a decomposition of the wage gap into differences due to endowments or observable characteristics ($\mathbb{E}$), those attributable to coefficients or unobservable effects ($\mathbb{C}$), and the interaction term between the differences in coefficients and differences in endowments ($\mathbb{CE}$), at various points of the wage distribution of the entire population, allowing the effect of endowments to differ over the distribution of the outcome (Fortin et al. 2011). Finally, the non-linear decomposition developed by Yun (2004) is employed to explore ethnic differences in the prevalence of informal employment.

Empirical Methodology

The first part of this study uses the conditional quantile regression decomposition as developed by Melly (2006).¹ This technique is derived from the Machado-Mata (2005) decomposition and it allows the difference in $\mathbb{Y}$ (log-wages) between groups $\mathbb{I}$ (indigenous) and $\mathbb{NI}$ (non-indigenous) to be decomposed as follows. First, let $Q_{\theta}(W_i|x_i)$ denote the θ^{th} conditional quantile of the distribution of the log-wage (Melly 2006; Machado and Mata 2005). Consequently, the wage gap between the indigenous and the non-indigenous population at the quantile distribution can be defined as:

$$Q_\theta(\bar{Y}) - Q_\theta(\bar{Y}^I) = \underbrace{[Q_\theta((\bar{X}_I - \bar{X}_{NI})\beta_{NI})]}_B + \underbrace{Q_\theta(\bar{X}_{NI}(\beta_I - \beta_{NI}))}_C + \underbrace{Q_\theta((\bar{X}_I - \bar{X}_{NI})(\beta_I - \beta_{NI}))}_{CE} + \bar{e}_I - \bar{e}_{NI}$$

The quantile regression decomposition technique developed by Melly (2006) is useful for contemplating variations in the ethnic wage gap at different points of the wage distribution; however, a limitation of this technique is that it does not allow for a detailed decomposition of the effects of characteristics and coefficients. Furthermore, it is important to highlight that this approach relies on the linearity of the quantile regression model and assumes that all covariates are exogenous (Melly 2006; Fortin et al. 2011). Thus, in addition to Melly's (2006) conditional quantile regression decomposition, this study will employ a more novel procedure proposed by Firpo, Fortin, and Lemieux (2009) to estimate a detailed unconditional quantile decomposition of the ethnic wage gap in Mexico.

The Firpo, Fortin, and Lemieux (2009)² decomposition consists of a standard regression in which the dependent variable, in this case the respondents' *log wage*, is transformed to be replaced by its (re-centered) influence function (RIF) (Firpo et al. 2009). This approach can be easily estimated as an ordinary least square (OLS) regression where the RIF of the unconditional quantile of the *log wage* can be modelled as a linear function of the explanatory variables. Hence, the RIF function, for a given quartile Q_θ can be computed as follows:

$$RIF(W, Q_\theta) = Q_\theta + \frac{\theta - \mathbb{I}\{W < Q_\theta\}}{f_w(Q_\theta)}$$

Where $f_w(Q_\theta)$ is the density function evaluated at a given quantile by using a kernel density approach and $\mathbb{I}\{W < Q_\theta\}$ is an indicator function that takes a value of one when W (or the respondents' *log wage*) is less than Q_θ . Thus, the expected value of the RIF regression can be thought of as an unconditional quantile regression. Then, a final step consists of estimating the coefficients of the unconditional quantile regression for groups $\mathbb{I}$ (indigenous) and $\mathbb{NI}$ (non-indigenous) to decompose them by employing the OB decomposition approach for each quantile.

Despite its advantages, a drawback of employing the Firpo, Fortin, and Lemieux (2009) approach is that it relies on the linear approximation of a non-linear distribution function. Furthermore, as with the conditional quantile decomposition developed by Melly (2006), this technique also assumes that all covariates are exogenous, and it does not account for endogeneity (Fortin et al. 2011). Nonetheless, unlike the Machado-Mata (2005) and Melly (2006) decompositions, the Firpo, Fortin, and Lemieux (2009) technique is able to estimate each covariate's effect along the different quantiles of the wage distribution (Firpo et al. 2009).

In the case of the traditional OB decomposition and both quantile decomposition techniques, the analysis employs the *indigenous* variable—whether a person reported speaking an indigenous tongue—as its key or focal independent variable. The dependent variable in the study is the respondents' *log wage*. For the analysis of the ethnic gap in the prevalence of informal

employment, the independent variable is a binary variable indicating participation in the informal sector. To control for mainstream predictors of labor market income as specified in Mincer's human capital earnings model, the model includes years of schooling and years of work experience and its square (Mincer 1976). A variable for work experience is not available in the ENIGH database, but for the purposes of this analysis, the potential work experience has been calculated as the difference between an individual's age (in years) and that individual's years of schooling plus six years; the age at which students generally begin elementary school. Given that much of the variation in wages can be explained by differences in the local labor market conditions, the model also includes size of the locality and state controls to account for geographic and rural/urban differences that could potentially explain ethnic wage disparities. Finally, occupational controls have been incorporated for twenty employment categories, according to the North American Industry Classification System (NAICS) (INEGI 2018).³ Additionally, controls are added for gender and the total number of hours worked per week.

Since this study also attempts to analyze why a higher proportion of the indigenous population is associated with employment in Mexico's informal sector, the final part of the analysis decomposes the observed indigenous/non-indigenous difference in the prevalence of informal employment by using a logistic model. As such, this study employs a decomposition procedure developed by Yun (2004) that extends the OB decomposition to a non-linear model (Powers et al. 2011; Yun 2004). This procedure employs weights obtained from a first-order Taylor linearization to avoid path dependency, and exactly decomposes the difference in the average observed binary outcomes (Fairlie 2016; Yun 2004). The logit model for the ethnic decomposition of the gap in the prevalence of informal employment considers the same predictors employed above. The binary dependent variable used to capture informality is constructed using ENIGH's self-reported data on access to social security benefits. According to INEGI's definition—which follows the criteria proposed by the International Labor Organization (ILO)—a wage earner whose job does not provide him or her with access to any type of social security benefits is said to work in the informal sector (Alcaraz et al. 2015).

4. Results and Discussion

The Oaxaca-Blinder Wage Decomposition by Ethnicity

Consistent with the empirical literature, this study shows strong bivariate associations between being indigenous and having lower wage levels. Results from the two-fold OB⁴ wage decomposition for each variable are shown below in **Figure 2**, with error bars that indicate 95 percent confidence intervals. It is important to note that the choice of the reference group is arbitrary, and it should be determined according to the structure of the researcher's problem (Jann 2008). All the decomposition analyses presented in this study have been produced with indigenous peoples as the reference group. Furthermore, given that indigenous peoples are likely to self-select into occupationally activities that predominantly occur without pay

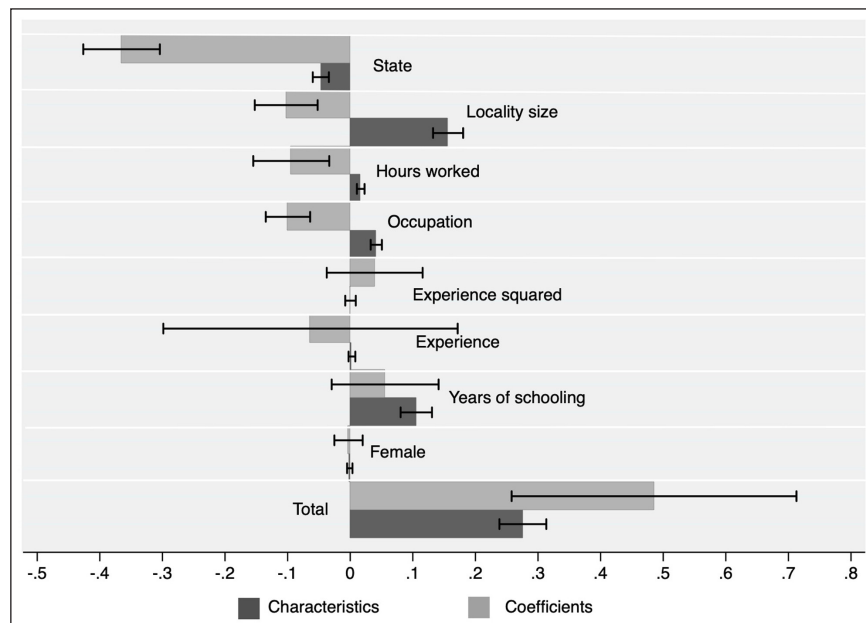


Figure 2: Two-fold Oaxaca-Blinder Wage Decomposition Results.

Notes: Indigenous is the reference category. Results show Heckman Correction estimates and bootstrapped standard errors with 50 replications.

Source: Author's calculations based on the ENIGH 2016.

and outside the labor force, the Heckman Selection Correction model is used in the OB decomposition to deal with the selectivity issue that is most likely to arise when decomposing wages (Jann 2008).

The traditional OB decomposition with data from the 2016 ENIGH reveals that the ethnic wage gap in Mexico is 82.8 percent. Once the Heckman Correction method has been applied to the decomposition to correct for any selection-bias, the gap decreases to 77.9 percent. Nearly 62.8 percent of the total ethnic wage gap (77.9 percent) is due to the unexplained component, while the remaining 37.2 percent can be explained by differences in the demographic, human capital, and occupational characteristics that are accounted for in this model. This indicates that numerous unobservable factors not included in the model (e.g. language barriers, quality of education, lack of social networks, and most likely labor market discrimination) could be affecting a significant proportion of the earnings disparity.

Figure 2 shows the detailed two-fold OB wage decomposition estimation results along with error bars that represent confidence intervals. As indicated in **Figure 2**, non-indigenous peoples display higher returns to human capital. Decomposition estimates show that inequalities in indigenous peoples' years of education and the size of the labor market largely explain wage disparities between both groups; if indigenous peoples had the same levels of schooling as the non-indigenous population, their wage gap would be reduced by 11 percent. Similarly, if indigenous peoples resided in localities with larger populations, the wage gap would be reduced by nearly 16 percent. In addition, a negative sign in the unexplained component indicates that the wealth gap narrows when applying the indigenous peoples' characteristics coefficients to the non-indigenous population. In this case, in terms of

coefficients, the negative and statistically significant coefficients for hours worked, occupation, size of the locality, and state indicate that the pay gap would narrow if non-indigenous peoples had the same returns to those characteristics as the indigenous group. For example, if they were to reside predominantly in rural localities, the indigenous pay gap would decrease. Yet, the size of the locality does not affect the non-indigenous population as much as it affects indigenous workers.

Furthermore, when disaggregating the OB wage decomposition results by gender, it is possible to observe that indigenous women experience a "double" penalty in the Mexican labor market. Once the Heckman technique has been applied to the OB wage decomposition to correct for possible selection bias, the ethnic wage gap appears to be nearly 4 times greater for indigenous women than for indigenous men. Both the occupational segregation of women and differences in years of work experience largely explain this disparity. However, while 73.4 percent of the ethnic wage gap in the case of women cannot be explained by differences in characteristics, only 12.5 of the male gap remains unexplained. This suggests that indigenous women in Mexico are more disadvantaged than men, given that they are likely to face discrimination on the basis of both their ethnicity and their sex. The decomposition results broken down by gender are presented in Table A1 in the appendix.

The Quantile Wage Decomposition by Ethnicity

Figure 3 underscores that the raw ethnic wage gap in Mexico does not remain constant across each wage distribution quantile. On the contrary, the wage gap varies significantly at different points of the distribution, indicating that the pay gap between indigenous and non-indigenous

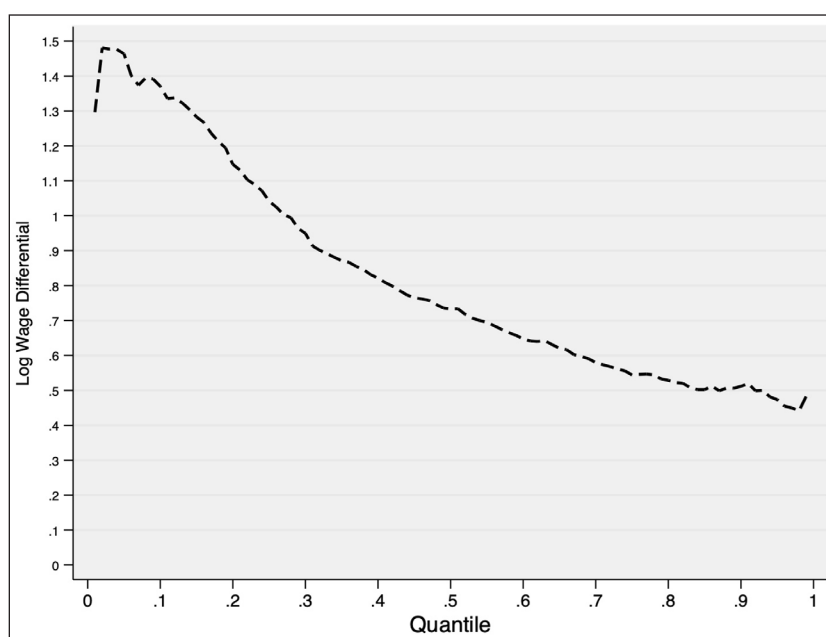


Figure 3: Mexico's Raw Ethnic Wage Gap, 2016.

Source: Author's calculations based on the ENIGH 2016.

peoples is high at low ranges of the wage distribution, but the gap narrows as income increases. Thus, to further our understanding of the ethnic wage gap in Mexico, it is important to analyze how the wage differentials between observable human capital characteristics and unexplained characteristics—which could reflect indigenous discrimination in the Mexican labor market—change at different quantiles of the distribution.

Table 2 shows results for the Melly (2006) and Firpo, Fortin, and Lemieux (2009) quantile wage decompositions. Overall, the decomposition of the ethnic pay differential across the wage distribution indicates statistically significant pay differences at all levels of the wage-distribution. In addition, both characteristics and coefficients play an important part in explaining the total gap, and their effects are significantly different from zero in all of the estimated deciles. Findings from Melly's (2007) decomposition show that the “unobserved” component explains a larger share of the wage gap at the lower end of the distribution; as we move to the top of the distribution, differences in characteristics or human capital endowments account for a larger share of the indigenous pay gap. While the percentage of the unexplained differential significantly decreases as we move from the left to the right side of the distribution, the percentage of the explained differential (due to differences in human capital endowments) remains considerably stable, displaying only marginal declines after the third quantile, as illustrated in **Figure 4**.

These results suggest that observable inequalities with regards to human-capital endowments and employment characteristics account for a significant proportion of the gap at all levels of the wage distribution, rising from 42.9 percent at the 10th percentile to 76.6 percent at the 90th percentile. On the other hand, the findings also imply that if labor market discrimination is present among these “unobservables,” then the penalty for being indigenous in

the Mexican labor market is highest in lowering-paying jobs, which usually exist in Mexico's informal economy. In the first and the second percentile, the unexplained component accounts for a large share of the gap (36 percent and 41 percent, respectively). Nonetheless, at higher levels of the distribution, it is differences in observable characteristics that largely explain these wage differentials. These results are further depicted in **Figure 4**, where the plots show the coefficient estimates for the ethnic wage gap at each decile of the wage distribution, as well as the contribution of the explained (characteristics) and the unexplained (coefficients) components to the overall gap.

As further indicated in **Table 2**, the Firpo, Fortin, and Lemieux (2009) unconditional quantile wage decomposition results clearly approximate those obtained through the Melly (2006). The detailed decomposition results produced by the RIF-OLS methodology illustrate to a greater extent the contribution of each variable to the overall gap at different levels of the wage distribution. At all levels of the distribution, non-indigenous peoples display higher returns to human capital. Furthermore, differences in indigenous peoples' years of education, occupations, and the size of the labor market largely explain wage disparities between both groups. However, it is mostly differences in characteristics, rather than a differential treatment in the labor market, that explains the ethnic wage gap towards the end of the wage distribution. Yet, differences in returns to education appear to account for a greater share of the gap at the 80th and 90th quantiles. By contrast, at lower quantiles of the wage distribution, there does not seem to be a consistent relationship between earnings and human capital accumulation, as work experience is not rewarded the same as in the case of non-indigenous peoples. What is more, differences in years of work experience, occupation, and geographical differences largely explain the sizeable wage gap, as indicated by the negative and statistically significant coefficient estimates for those variables.

Table 2: Conditional and unconditional quantile wage decomposition results.

Quantile	$\theta = .10$	$\theta = .20$	$\theta = .30$	$\theta = .40$	$\theta = .50$	$\theta = .60$	$\theta = .70$	$\theta = .80$	$\theta = .90$
Decomposition Method: Machado and Mata (2005) – Melly (2006)									
Raw Difference	–1.33*** (0.02)	–1.13*** (0.02)	–0.97*** (0.02)	–0.85*** (0.01)	–0.75*** (0.01)	–0.67*** (0.01)	–0.61*** (0.01)	–0.54*** (0.01)	–0.47*** (0.02)
Characteristics	–0.57*** (0.01)	–0.49*** (0.01)	–0.45*** (0.01)	–0.43*** (0.01)	–0.41*** (0.01)	–0.40*** (0.01)	–0.39*** (0.01)	–0.38*** (0.01)	–0.36*** (0.01)
Coefficients	–0.48*** (0.02)	–0.46*** (0.02)	–0.44*** (0.02)	–0.42*** (0.01)	–0.39*** (0.01)	–0.36*** (0.01)	–0.32*** (0.01)	–0.28*** (0.02)	–0.22*** (0.02)
Decomposition Method: Firpo, Fortin, and Lemieux (2009) – RIF Regressions									
Raw Difference	1.41*** (0.03)	1.16*** (0.03)	0.96*** (0.02)	0.83*** (0.02)	0.72*** (0.02)	0.65*** (0.01)	0.58*** (0.01)	0.52*** (0.01)	0.50*** (0.01)
Characteristics									
Female	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00* (0.00)	0.00* (0.00)	0.00* (0.00)	0.00 (0.00)
Years of schooling	0.07** (0.03)	0.09*** (0.02)	0.13*** (0.02)	0.14*** (0.02)	0.15*** (0.01)	0.15*** (0.01)	0.16*** (0.01)	0.17*** (0.01)	0.20*** (0.02)
Experience	–0.24*** (0.04)	–0.20*** (0.03)	–0.12*** (0.02)	–0.07*** (0.02)	–0.07*** (0.02)	–0.03* (0.01)	–0.02 (0.01)	–0.02 (0.01)	–0.02 (0.01)
Experience squared	0.38*** (0.04)	0.29*** (0.03)	0.18*** (0.02)	0.11*** (0.02)	0.09*** (0.01)	0.05*** (0.01)	0.03* (0.01)	0.01 (0.01)	0.00 (0.01)
Occupation	0.16*** (0.01)	0.18*** (0.01)	0.17*** (0.01)	0.14*** (0.01)	0.12*** (0.01)	0.12*** (0.01)	0.10*** (0.01)	0.07*** (0.01)	0.06*** (0.01)
Hours worked	0.05*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.05*** (0.00)	0.04*** (0.00)	0.04*** (0.00)	0.03*** (0.00)	0.03*** (0.00)	0.02*** (0.00)
Locality size	0.21*** (0.02)	0.26*** (0.02)	0.28*** (0.02)	0.27*** (0.01)	0.24*** (0.01)	0.22*** (0.01)	0.23*** (0.02)	0.20*** (0.02)	0.19*** (0.02)
State	–0.10*** (0.01)	–0.09*** (0.01)	–0.11*** (0.01)	–0.08*** (0.01)	–0.07*** (0.01)	–0.06*** (0.01)	–0.05*** (0.01)	–0.03*** (0.01)	–0.02*** (0.01)
Coefficients									
Female	0.03 (0.03)	0.01 (0.02)	–0.02 (0.02)	–0.02 (0.01)	–0.02 (0.01)	–0.03* (0.01)	–0.03** (0.01)	–0.04** (0.01)	–0.03** (0.01)
Years of schooling	0.05 (0.07)	0.05 (0.05)	0.01 (0.04)	0.03 (0.03)	0.04 (0.03)	0.07* (0.03)	0.09** (0.03)	0.11** (0.03)	0.16 (0.04)
Experience	–0.55** (0.19)	–0.77*** (0.14)	–0.51*** (0.11)	–0.35*** (0.08)	–0.33*** (0.07)	–0.18** (0.07)	–0.11 (0.07)	–0.06 (0.07)	0.00 (0.07)
Experience squared	0.19 (0.13)	0.50*** (0.09)	0.33*** (0.07)	0.22*** (0.05)	0.22*** (0.04)	0.14*** (0.04)	0.11** (0.04)	0.07* (0.04)	0.05 (0.04)
Occupation	–0.13*** (0.03)	–0.22*** (0.02)	–0.23*** (0.02)	–0.18*** (0.02)	–0.17*** (0.01)	–0.17*** (0.01)	–0.15*** (0.01)	–0.11*** (0.01)	–0.09*** (0.02)
Hours worked	0.25*** (0.06)	–0.12** (0.05)	–0.17*** (0.04)	–0.19*** (0.03)	–0.16*** (0.03)	–0.18*** (0.03)	–0.15*** (0.03)	–0.15*** (0.03)	–0.07** (0.03)
Locality size	0.00 (0.04)	–0.18*** (0.03)	–0.23*** (0.03)	–0.25*** (0.02)	–0.21*** (0.02)	–0.20*** (0.02)	–0.23*** (0.03)	–0.20*** (0.03)	–0.22*** (0.03)
State	–0.64*** (0.06)	–0.60*** (0.05)	–0.67*** (0.04)	–0.52*** (0.03)	–0.49*** (0.03)	–0.40*** (0.03)	–0.35*** (0.03)	–0.28*** (0.03)	–0.23*** (0.03)

Notes: N = 105,754; * p < 0.05, ** p < 0.01, *** p < 0.001; Bootstrap standard errors with 100 replications in parenthesis.

Source: Author's calculations based on the ENIGH 2016.

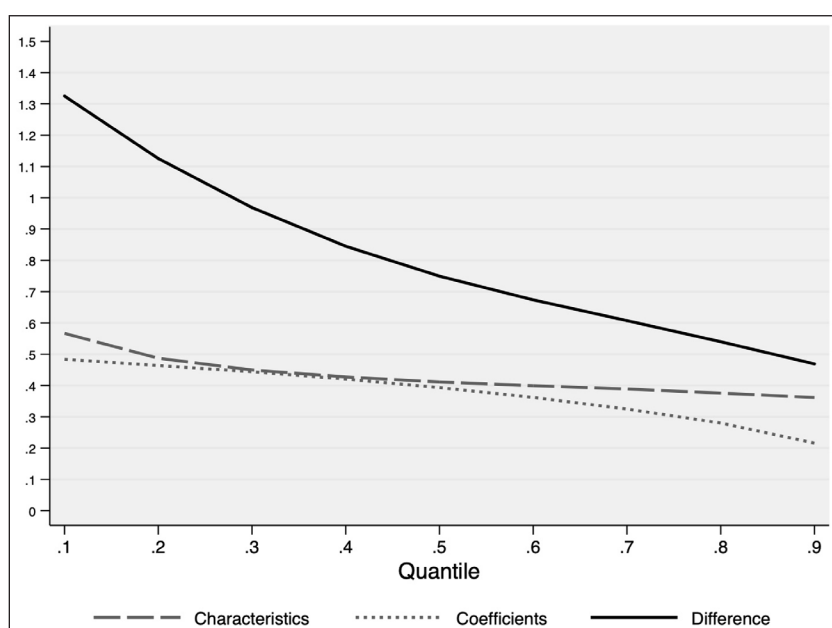


Figure 4: Quantile Decomposition of Mexico's Ethnic Wage Gap, 2016.
Source: Author's calculations based on the ENIGH 2016.

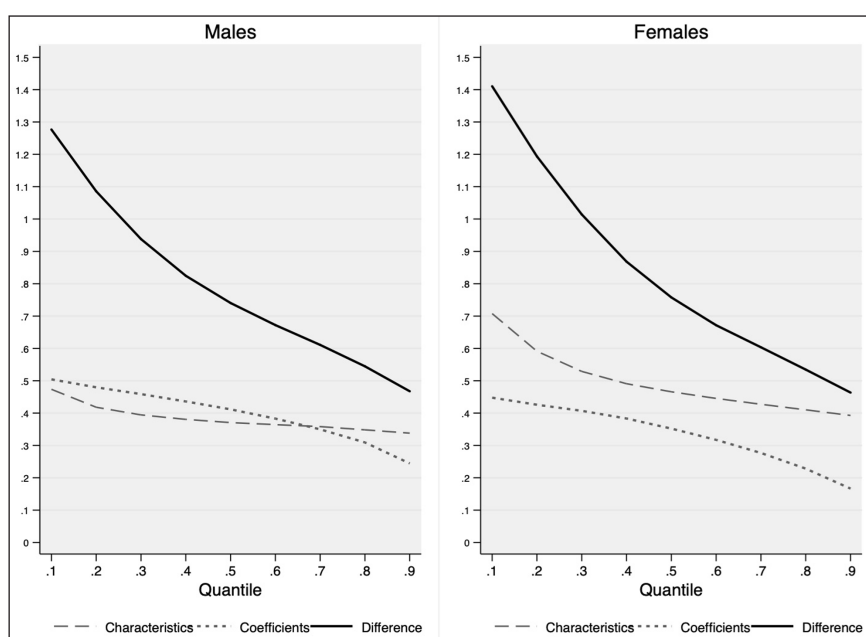


Figure 5: Quantile Decomposition of Mexico's Ethnic Wage Gap by Gender, 2016.
Source: Author's calculations based on the ENIGH 2016.

If we disaggregate the conditional quantile decomposition analysis of ethnic wage gap across gender, once again, we observe that there is a greater wage gap for indigenous women. **Figure 5** depicts Melly's (2006) decompositions of the ethnic wage gap in Mexico for both men and women. Two important points emerge from these plots. First, the ethnic wage gap is more severe for women at lower quantiles of the wage distribution, while it appears to be more equitable across genders at the top of the wage distribution. Second, differences in characteristics account for a larger share of the ethnic wage gap along the entire distribution when the sample is restricted to females. This suggests that most of the wage gap between indigenous and non-indigenous women can be explained

by differences in endowments (or characteristics). This is unsurprising, given that there are significant disparities in terms of access to education between men and women in Mexico's indigenous communities (Parker et al. 2002). On the other hand, the ethnic wage gap in the case of men appears to be driven by both differences in characteristics and coefficients, with the unexplained component playing a larger role in the lower half of the wage distribution.

Differences in The Prevalence of Informality

A final step is to decompose the observed indigenous/non-indigenous difference in the prevalence of informal employment. This will further our understanding of the indigenous wage gap and corroborate whether

differences in observed characteristics between both groups can explain the overrepresentation of indigenous peoples in the Mexican informal economy. As mentioned earlier, not having access to social security is regarded as an indicator that the worker was not hired following labor regulations and is therefore working informally (INEGI 2005). This definition does not exclude informal workers who work for a formal firm that is legally registered in terms of its tax obligations. It is important to note that the model presented in this analysis adopts reference categories for the state, locality size, and occupation categorical variables included in the analysis. Thus, if a different reference category were chosen, both these variables' coefficients and the intercept would change. To overcome this limitation, the model is fitted using an ANOVA-type normalization in which the coefficients in the logistic regression model sum to zero across levels of each of the three abovementioned categorical variables that are included in the model (Powers et al. 2011).

Findings from the two-fold decomposition normalized model of the prevalence of employment in the informal sector are shown in **Figure 6**. Results indicate a smaller gap (31.2 percent) with regards to employment in the informal sector, in comparison to the ethnic wage gap. However, 52 percent of the gap in the prevalence of employment in the informal sector between indigenous and non-indigenous peoples is due to the unexplained component, with differences in endowments accounting for the remaining 48 percent. Once again, differences in years of schooling between both groups account for a significant portion of the explained part of the ethnic gap in the prevalence of informal employment (73 percent). A less important proportion of the differences in endowments (characteristics) component is due to urban/rural differences, meaning differences in the size of the locality.

With regards to the (unexplained) coefficients component, **Figure 6** shows that all variables except hours worked achieve clear statistical significance. In this case, the gap in the prevalence of informal work that is attributable to the coefficients is largely driven by differences in returns to schooling, followed by years of work experience. In terms of geographical differences, the findings show that if non-indigenous peoples were to reside in the same states where indigenous peoples predominantly reside, the ethnic gap in the prevalence of informal employment would narrow. Similar results can be observed for occupation, indicating that indigenous peoples in Mexico are occupationally segregated into activities that predominantly occur outside the formal economy. Interestingly, the positive unexplained coefficient for females reveals that indigenous women have a lower prevalence of informal employment than their non-indigenous counterparts.

Table 3 reports findings from the two-fold decomposition normalized model of the prevalence of employment in the informal sector by ethnicity and across gender. As indicated above in **Figure 6**, the ethnic gap in the prevalence of informal employment is larger for men than it is for women. However, unlike the wage gap, differences in formal employment in the case of indigenous women appear to be more related to unexplained components that could be reflective of entrenched discrimination towards women when attempting to access the formal labor market. Furthermore, when the sample is restricted to females rather than males, a larger proportion of the gap cannot be explained by differences in observable characteristics. In addition, according to the detailed decomposition, this component of the gap is explained the most by state differences, suggesting that, unlike indigenous men, indigenous women are less likely to migrate and tend to remain in their communities of origin, where the barriers to entry to formal employment are highest.

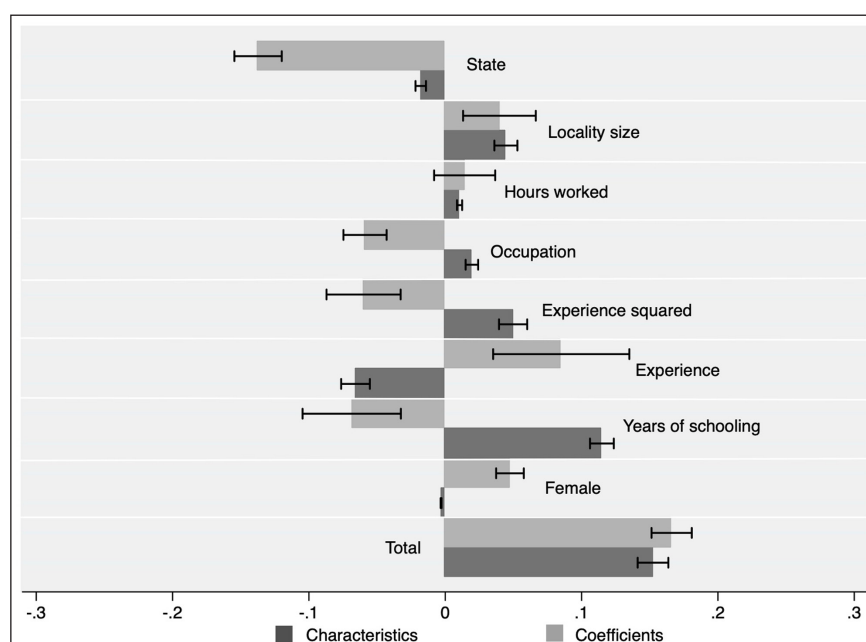


Figure 6: Decomposition Results of the Prevalence of Employment in the Informal Sector.
Source: Author's calculations based on the ENIGH 2016.

Table 3: Decomposition Results of the Ethnic Gap in the Prevalence of Informal Employment by Gender.

	Total Sample	Females	Males
Raw Difference	0.32*** (0.00)	0.28*** (0.01)	0.37*** (0.01)
Characteristics	0.15*** (0.01)	0.14*** (0.01)	0.19*** (0.01)
Coefficients	0.17*** (0.01)	0.15*** (0.01)	0.18*** (0.01)
Detailed decomposition			
Characteristics			
Female	0.00*** (0.00)	—	—
Years of schooling	0.11*** (0.00)	0.10*** (0.00)	0.14*** (0.01)
Experience	−0.07*** (0.01)	−0.07*** (0.01)	−0.08*** (0.01)
Experience squared	0.05*** (0.01)	0.05*** (0.01)	0.08*** (0.01)
Occupation	0.02*** (0.00)	0.03*** (0.00)	0.00 (0.00)
Hours worked	0.01*** (0.00)	0.01*** (0.00)	0.02*** (0.00)
Locality size	0.04*** (0.00)	0.06*** (0.01)	0.02** (0.01)
State	−0.02*** (0.00)	−0.03*** (0.00)	0.00 (0.00)
Coefficients			
Female	0.05*** (0.01)	—	—
Years of schooling	−0.07*** (0.02)	−0.06** (0.02)	−0.12*** (0.03)
Experience	0.09*** (0.03)	0.10** (0.03)	0.02 (0.05)
Experience squared	−0.06*** (0.01)	−0.06*** (0.02)	−0.02 (0.03)
Occupation	−0.06*** (0.01)	−0.05*** (0.01)	−0.04* (0.02)
Hours worked	0.01 (0.01)	0.02 (0.02)	−0.02 (0.02)
Locality size	0.04*** (0.01)	0.01 (0.02)	0.11*** (0.03)
State	−0.14*** (0.01)	−0.18*** (0.01)	−0.04* (0.02)
N	130051	78402	51649

Notes: N = 76,001; * p < 0.05, ** p < 0.01, *** p < 0.001; Bootstrap standard errors with 100 replications in parenthesis.

Source: Author's calculations based on the ENIGH 2016.

5. Conclusions and Policy Implications

This paper contributes to the existing literature on the ethnic wage gap in Mexico by examining pay disparities between indigenous and non-indigenous peoples across the wage distribution using two novel quantile decomposition techniques. In addition, this study further investigates the high incidence of informal employment among indigenous peoples in Mexico by decomposing the gap in the prevalence of informal employment at the indigenous and non-indigenous peoples group means. Furthermore, the decomposition analyses are then disaggregated across gender to examine whether indigenous men and women face different labor market penalties.

Overall, the findings of this study are threefold. First, the empirical evidence drawn from the wage decompositions by ethnicity shows that even though most of the ethnic wage gap can be explained by differences in human capital endowments, particularly years of schooling, differences in coefficients account for a significant proportion of the pay gap in Mexico. This indicates that indigenous disadvantage would persist even if human capital outcomes improved for this population subgroup. What is more, the Melly (2006) and Firpo, Fortin, and Lemieux (2009) quantile wage decompositions indicate that the penalty for being indigenous is more pronounced at low levels of the wage distribution, suggesting low-wage indigenous workers are more penalized in the Mexican labor market. Second, the logistic decomposition of the average likelihood of informal employment between indigenous and non-indigenous peoples indicates that nearly 53 percent of the gap in the prevalence of informal employment remains unexplained. Thus, while the accumulation of human capital is a necessary condition for bridging the ethnic wage gap, it is not in itself sufficient; occupational and spatial segregation and labor market discrimination continue to play an important role. Third, indigenous women experience a “double” wage penalty in the Mexican labor force. On the one hand, the ethnic wage gap is significantly higher for women than for men, particularly at lower levels of the wage distribution. Most of this wage differential can be explained by differences in observable characteristics, given that indigenous women are often confined to traditional roles that inhibit their human capital accumulation. On the other hand, while the ethnic gap in the prevalence of formal employment is lower for indigenous women than for indigenous men, in the case of women, a larger proportion of the gap is due to the unexplained component, suggesting that gender discrimination may be most prevalent in formal jobs.

The results summarized above are consistent with those presented in previous literature (Aguilar-Rodriguez et al. 2018; Cano-Urbina and Mason 2016; Hisamatsu and Ukeda 2002). While studies that decompose the indigenous pay gap in Mexico reach similar estimates of statistical discrimination (around 40 percent of the ethnic wage gap cannot be accounted by differences in observed characteristics), other measures of indigenous discrimination in the Mexican labor market have been well documented. For example, Flores and Telles (2012) conducted an experimental survey of skin-color phenotypes, concluding that indigenous disadvantage with regards to education

and labor markets is largely determined by skin color (Flores and Telles 2012). More recently, Arceo-Gomez and Campos-Vazquez (2014) conducted a field experiment of fictitious CVs, finding evidence of discrimination against indigenous-looking women in the Mexican formal labor market (Arceo-Gomez and Campos-Vazquez 2014).

It is important to note that one potential limitation of this study concerns the indigenous identification strategy. Throughout this study, the self-identification as a person who speaks an indigenous language was used as a key variable, the criterion the Mexican Census and the CDI use to identify an individual as indigenous (Navarrete Linares 2008). Results from this study were replicated using self-identification as an indigenous person rather than speaking an indigenous language: similar results were obtained, with more pronounced ethnic gaps in both differences in endowments and coefficients, and a slightly narrower indigenous gap in the prevalence of informal employment. Nonetheless, excluded from this analysis are those ENIGH respondents who chose not to identify as indigenous but who, as the literature points out, are vulnerable to experiencing discrimination in the labor market due to physical characteristics such as the tone of their skin (Arceo-Gomez and Campos-Vazquez 2014; Flores and Telles 2012).

Taken together, the results from this study highlight the need for an institutional framework that better addresses indigenous rights, specifically in the informal sector, and social policies that improve equal accumulation of human capital. Although Mexico has made significant progress with regards to its antidiscrimination laws,⁵ findings from this study suggest that integration and labor-market policies aimed at improving the employment and pay prospects of indigenous peoples need to go beyond strengthening the legal system. While establishing

standards for labor equality and non-discrimination is critical, the majority of indigenous workers remain employed outside the scope of Mexico's legal frameworks. Given that this analysis shows a significant gap in the prevalence of informal employment among indigenous waged-workers, and that "unobserved" differences account for a significant proportion of the ethnic gap at lower levels of the wage distribution (1st through 3rd decile), it can be concluded that indigenous workers are disproportionately located in what are most likely informal jobs, where labor regulations are inexistent.

In addition, the sizeable gap between the average education level of indigenous and non-indigenous peoples (7 versus 10 years) highlights the need for public policies to better address these inequalities and promote quality education for rural and isolated indigenous communities. Currently, Mexico's public education is imparted in Spanish, completely disregarding the special needs of many indigenous children who speak only their native tongues. The lack of bilingual teachers and bicultural education materials plays a key role in preventing the closing of the indigenous gap in years of schooling. Therefore, improved education policies need to be accompanied by government actions that seek to improve the living conditions of indigenous peoples, such as enhancing access to social healthcare and supporting social programs that promote equal opportunities and disincentivize child labor participation. Furthermore, particular consideration needs to be given to gender inequality in education amongst indigenous children. Traditional social structures in many Mexican indigenous communities continue to keep indigenous girls out of school, leading to their unequal participation in the labor market (Osorio Vázquez 2017).

Appendix

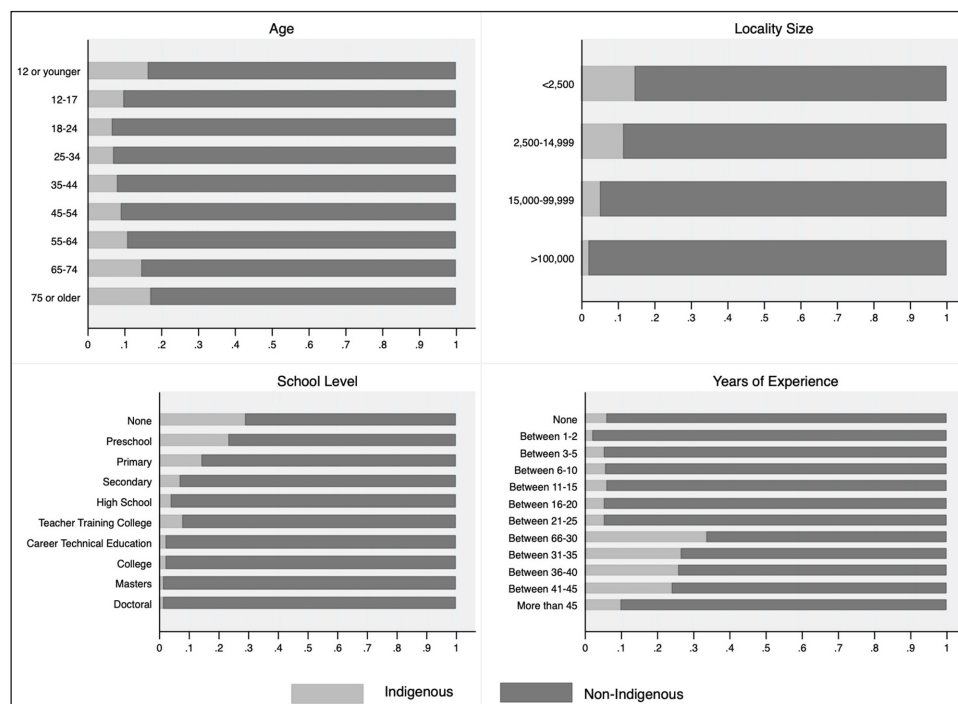


Figure A1: Structure of the Population by Socio-economic Characteristics.
Source: Author's calculations based on the ENIGH 2016.

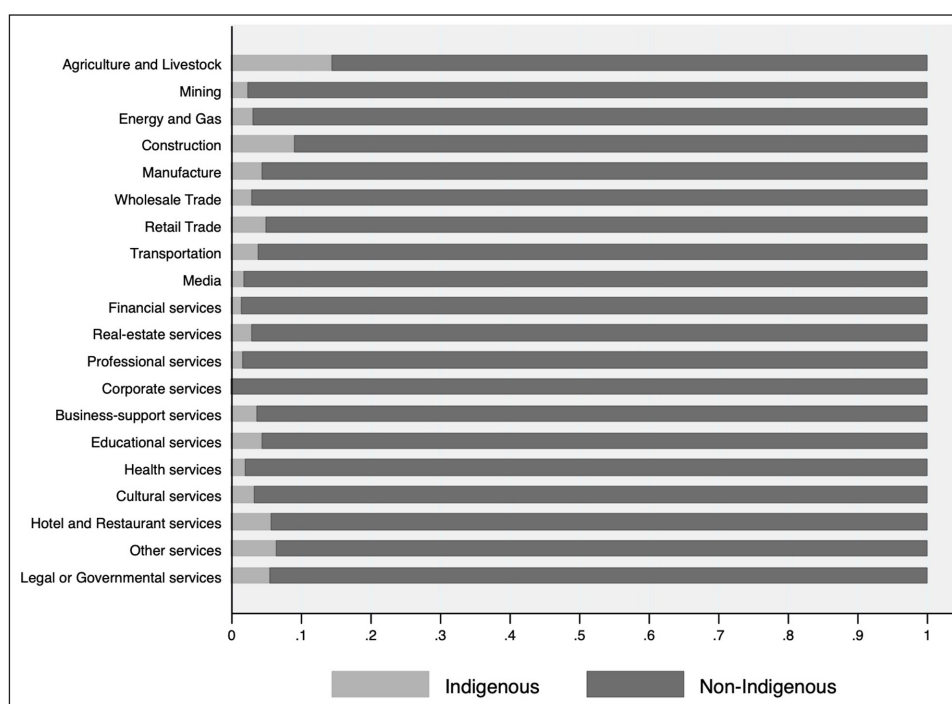


Figure A2: Structure of the Population by Occupational Sectors.

Source: Author's calculations based on the ENIGH 2016.

Table A1: Two-fold Oaxaca-Blinder Wage Decomposition Results.

	Total Sample		Females		Males	
	(1)	(2)	(1)	(2)	(1)	(2)
Raw Difference	0.83***	0.78***	0.85***	1.24***	0.81***	0.32
	(0.01)	(0.12)	(0.02)	(0.17)	(0.02)	(0.17)
Characteristics	0.51***	0.28***	0.57***	0.27***	0.46***	0.30***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Coefficients	0.38***	0.49***	0.33***	0.91***	0.41***	0.04
	(0.01)	(0.12)	(0.02)	(0.17)	(0.02)	(0.17)
Characteristics						
Female	0.00	0.00	—	—	—	—
	(0.00)	(0.00)	—	—	—	—
Years of schooling	0.14**	0.11***	0.16***	0.11***	0.11***	0.11***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Experience	-0.11***	0.00	-0.13***	0.01	-0.10***	0.03*
	(0.01)	(0.00)	(0.03)	(0.01)	(0.02)	(0.01)
Experience squared	0.15***	0.00	0.19***	0.02**	0.13***	-0.02**
	(0.01)	(0.00)	(0.02)	(0.01)	(0.02)	(0.01)
Occupation	0.12***	0.04***	0.13***	0.02***	0.11***	0.04***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Hours worked	0.04**	0.02***	0.07***	0.03***	0.03***	0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Locality size	0.23***	0.16***	0.23***	0.14***	0.22***	0.16***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
State	-0.06***	-0.05***	-0.08***	-0.06***	-0.05***	-0.04***

(Contd.)

	Total Sample		Females		Males	
	(1)	(2)	(1)	(2)	(1)	(2)
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Coefficients						
Female	−0.01	0.00	—	—	—	—
	(0.01)	(0.01)	—	—	—	—
Years of schooling	0.08**	0.06	0.06	0.08	0.09*	−0.01
	(0.03)	(0.04)	(0.04)	(0.06)	(0.04)	(0.06)
Experience	−0.31***	−0.06	−0.26**	0.37*	−0.33***	−0.51*
	(0.07)	(0.12)	(0.11)	(0.18)	(0.08)	(0.17)
Experience squared	0.17***	0.04	0.12	−0.07	0.19***	0.09
	(0.04)	(0.04)	(0.06)	(0.07)	(0.05)	(0.05)
Occupation	−0.14***	−0.10***	−0.18***	−0.17***	−0.12***	−0.07***
	(0.01)	(0.02)	(0.02)	(0.04)	(0.01)	(0.02)
Hours worked	−0.07**	−0.09**	−0.07*	−0.12**	−0.09*	−0.08
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Locality size	−0.18***	−0.10***	−0.17***	−0.05	−0.19***	−0.12***
	(0.02)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)
State	−0.43***	−0.37***	−0.50***	−0.44***	−0.38***	−0.32***
	(0.03)	(0.03)	(0.04)	(0.06)	(0.03)	(0.04)
With Heckman Correction	N	Y	N	Y	N	Y
N	105,754	101,168	43,639	41,552	62,115	59,616

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Bootstrap standard errors with 100 replications in parenthesis.

Source: Author's calculations based on the ENIGH 2016.

Notes

- ¹ Conditional quantile decomposition results were calculated in Stata using the *rqdeco3* command, which is provided by Melly (2007).
- ² The Stata command *rifreg* was used to compute the unconditional quantile decomposition results.
- ³ The employment categories are the following: Agriculture and Livestock, Mining, Energy and Gas, Construction, Manufacture, Wholesale Trade, Retail Trade, Transportation, Media, Financial Services, Real-estate Services, Professional Services, Corporate Services, Business-support Services, Educational Services, Health Services, Cultural Services, Hotel and Restaurant Services, Legal or Governmental Services, and Other Services.
- ⁴ Two-fold decomposition results were calculated using the Stata *oaxaca* command as specified in Jann (2008).
- ⁵ In 2012, the Mexican Parliament unanimously passed a "Federal Law to Prevent and Eliminate Discrimination" (LFPED, in Spanish) that states that any distinction made against employees based on race, nationality, sex, age, disability, religion, migratory condition, health, sexual orientation, religion, political affiliation or social status is strictly prohibited.

Acknowledgements

The author would like to thank Peter Ward and Sophie Morse for their helpful comments on an early version of this paper and the journal's anonymous reviewers for their feedback.

Competing Interests

The author has no competing interests to declare.

References

- Aguilar-Rodriguez, A, Miranda, A and Zhu, Y.** 2018. Decomposing the language pay gap among the indigenous ethnic minorities of Mexico: Is it all down to observables? *Journal Economics Bull*, 38: 689–695.
- Alcaraz, C, Chiquiar, D and Salcedo, A.** 2015. Informality and Segmentation in the Mexican Labor Market, 2015–25. Mexico City, Mexico.
- Arceo-Gomez, EO and Campos-Vazquez, RM.** 2014. Race and Marriage in the Labor Market: A Discrimination Correspondence Study in a Developing Country. *Am. Econ. Rev.*, 5: 376–80. DOI: <https://doi.org/10.1257/aer.104.5.376>
- Blinder, AS.** 1973. Wage Discrimination: Reduced Form and Structural Estimates. *J. Hum. Resour.*, 8: 436–455. DOI: <https://doi.org/10.2307/144855>
- Cano-Urbina, J and Mason, PL.** 2016. Acculturation and the labor market in Mexico. *IZA Journal of Labor Policy*, 5.
- Castaneda-Navarrete, J.** 2013. Poverty Dynamics in Mexico, 2002–2005. An Ethnicity Approach. *Brazilian Rev. Econom.*, 33: 69–89. DOI: <https://doi.org/10.12660/bre.v33n12013.8944>
- CONEVAL.** 2010. Lineamientos y criterios generales para la definición, identificación y medición de la pobreza. Mexico City, Mexico.

- CONEVAL**. 2016. CONEVAL. Medición la Pobr. Available at: https://www.coneval.org.mx/Medicion/MP/Paginas/Pobreza_2016.aspx.
- Delaunay, D.** 2005. Análisis individual y contextual en la identificación de los pueblos indígenas (México, 1990–2000). Santiago, Chile.
- Fairlie, RW.** 2016. Addressing Path Dependence and Incorporating Sample Weights in the Nonlinear Blinder-Oaxaca Decomposition Technique for Logit, Probit and Other Nonlinear Models Robert.
- Firpo, S, Fortin, NM and Lemieux, T.** 2009. Unconditional Quantile Regressions. *Econometrica*, 77: 953–973. DOI: <https://doi.org/10.3982/ECTA6822>
- Flores, R and Telles, E.** 2012. Social Stratification in Mexico: Disentangling Color, Ethnicity, and Class. *Am. Sociol. Rev.*, 77: 486–494. DOI: <https://doi.org/10.1177/0003122412444720>
- Fortin, N, Lemieux, T and Firpo, S.** 2011. Decomposition Methods in Economics. In: Ashenfelter, O and Card, D (eds.), *Handbook of Labor Economics*, 1–102. Elsevier B.V, North Holland, Great Britain. DOI: [https://doi.org/10.1016/S0169-7218\(11\)00407-2](https://doi.org/10.1016/S0169-7218(11)00407-2)
- García-Aracil, A and Winter, C.** 2006. Gender and ethnicity differentials in school attainment and labor market earnings in Ecuador. *World Dev.*, 34: 289–307. DOI: <https://doi.org/10.1016/j.worlddev.2005.10.001>
- González de Alba, IG.** 2010. Poverty in Mexico from an Ethnic Perspective. *J. Hum. Dev. Capab.*, 11: 449–465. DOI: <https://doi.org/10.1080/19452829.2010.495518>
- Hall, G and Patrinos, HA.** 2004. Indigenous Peoples, Poverty and Human Development in Latin America: 1994–2004 – executive summary. Washington, D.C.
- Hisamatsu, Y and Ukeda, H.** 2002. Economic Disadvantage of Being Indigenous: An Analysis of Mexico's First National Survey of Employment in Indigenous. *Prepared for delivery at the 2003 meeting of the Latin American Studies Association*, Dallas, Texas, March 27–29, 2003 1–21.
- INEGI.** 2005. Encuesta Nacional de Ocupación y Empleo (ENOE): Metodología.
- INEGI.** 2018. North American Industry Classification System (NAICS). *Natl. Inst. Stat. Geogr.* Available at: http://naics-scian.inegi.org.mx/naics_scian/default_i.aspx.
- Jann, B.** 2008. The Blinder–Oaxaca decomposition for linear regression models. *Stata J.*, 8: 453–479. DOI: <https://doi.org/10.1177/1536867X0800800401>
- Liberato, ASQ, Pomeroy, C and Fennell, D.** 2006. Well-Being Outcomes in Bolivia: Accounting for the Effects of Ethnicity and Regional Location. *Soc. Indic. Res.*, 76: 233–262. DOI: <https://doi.org/10.1007/s11205-005-1098-5>
- Lunde, T, Skoufias, E and Patrinos, HA.** 2007. Indigenous Peoples In Latin America: Economic Opportunities And Social Networks, Policy Research Working Papers. Washington, D.C.
- Machado, JAF and Mata, J.** 2005. Counterfactual decomposition of changes in wage distributions using quantile regression. *J. Appl. Econom.*, 20: 445–465. DOI: <https://doi.org/10.1002/jae.788>
- McNeilly, J.** 2013. Measuring the Race Gap in Mexico: Evaluating Labor Market Outcomes between Ethnically Indigenous and Non-Indigenous Household Heads. Haverford College.
- Melly, B.** 2006. Estimation of counterfactual distributions using quantile regression. *Rev. Labor Econ.*, 68: 543–572.
- Melly, B.** 2007. Rqdeco: A Stata Module to Decompose Differences in Distribution. St. Gallen, Switzerland.
- Mincer, J.** 1976. Progress in Human Capital Analysis of the Distribution of Earnings. In: Atkinson, AB (ed.), *The Personal Distribution of Incomes*. Allen & Unwin, London, England. DOI: <https://doi.org/10.3386/w0053>
- Moreno, VA, Patrinos, G and Anthony, H.** 2011. Indigenous peoples and poverty in Mexico. Washington, D.C.
- Navarrete Linares, F.** 2008. Los pueblos indígenas de México. Mexico City, Mexico.
- Ñopo, HR.** 2012. New century, Old Disparities: Gender and Ethnic Earnings Gaps in Latin America and The Caribbean. Inter-American Development Bank, Washington, D.C. DOI: <https://doi.org/10.1596/978-0-8213-8686-6>
- Oaxaca, R.** 1973. Male-Female Wage Differentials in Urban Labor Markets. *Int. Econ. Rev.*, 14: 693–709. (Philadelphia). DOI: <https://doi.org/10.2307/2525981>
- Oaxaca, R and Ransom, M.** 1994. On discrimination and the decomposition of wage differentials. *J. Econom.*, 61: 5–21. DOI: [https://doi.org/10.1016/0304-4076\(94\)90074-4](https://doi.org/10.1016/0304-4076(94)90074-4)
- OECD.** 2016. OECD Reviews of Health Systems: Mexico 2016. Paris.
- OECD.** 2017. OECD Skills Strategy Diagnostic Report: Mexico 2017. Paris, France.
- Osorio Vázquez, MC.** 2017. Is social inclusion happening for indigenous girls in Mexico? Brookings Inst.
- Parker, SW, Rubalcava, L and Teruel, G.** 2002. Schooling inequality among the indigenous: A problem of resources or language barriers. Washington, D.C.
- Powers, D, Yoshioka, H and Yun, M.** 2011. mvdcmp: Multivariate decomposition for nonlinear response models. *Stata J.*, 11: 556–576. DOI: <https://doi.org/10.1177/1536867X1101100404>
- Psacharopoulos, G and Patrinos, HA.** (eds.) 1994. Indigenous People and Poverty in Latin America: An Empirical Analysis. World Bank, Washington, D.C. DOI: <https://doi.org/10.1596/0-8213-2958-8>
- Sandefur, GD and Pahari, A.** 1989. Racial and Ethnic Inequality in Earnings and Educational Attainment. *Soc. Serv. Rev.*, 63: 199–221. DOI: <https://doi.org/10.1086/603694>
- Wilson, D and Macdonald, D.** 2010. The Income Gap Between Aboriginal Peoples and the Rest of Canada. Ottawa, Canada.
- Yun, M.** 2004. Decomposing differences in the first moment. *Econ. Lett.*, 82: 275–280. DOI: <https://doi.org/10.1016/j.econlet.2003.09.008>

How to cite this article: Canedo, A. 2019. Labor Market Discrimination Against Indigenous Peoples in Mexico: A Decomposition Analysis of Wage Differentials. *Iberoamericana – Nordic Journal of Latin American and Caribbean Studies*, 48(1), pp. 12–27.
DOI: <https://doi.org/10.16993/iberoamericana.433>

Published: 01 March 2019

Copyright: © 2019 The Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC-BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited. See <http://creativecommons.org/licenses/by/4.0/>.



Iberoamericana – Nordic Journal of Latin American and Caribbean Studies is a peer-reviewed open access journal published by Stockholm University Press.

OPEN ACCESS The Open Access logo, consisting of a stylized 'O' and 'A' within a circle.