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Articles

Impact of migration on employment and wage distribution in Colombia

Impacto de la migración sobre el empleo y la distribución salarial en Colombia

Cristian Dario Castillo Robayo[a] https://orcid.org/0000-0001-7569-1860
William Prieto[b] https://orcid.org/0000-0001-7992-8781
Jacobo Alberto Campo Robledo[b]* https://orcid.org/0000-0003-3057-6206

[a] Universidad de los Llanos, Facultad de Economía, Villavicencio, Colombia, e-mail: cristian.castillo.robayo@unillanos.edu.co
[b] Universidad Católica de Colombia, Facultad de Ciencias Económicas y Administrativas, Bogotá, Colombia, e-mail: woprieto@ucatolica.edu.co, jacampo@ucatolica.edu.co

Abstract

This document presents empirical evidence to understand the impacts of migration on the labor market in Colombia, through the estimation of a multinomial logit-type model for employment and unconditional quantile regression for the effect on wages with information from 2015 to 2019. For both estimates, a difference in differences model is used in order to determine the effect of migration. The main conclusion of the study indicates evidence of an effect on the distribution of employment and wages that refer to the most vulnerable groups, with less education and informality, through an increase in competition in the unskilled labor segment. The effect on wages is limited, but more evident in the lowest income quartiles of the income distribution, with a significant drop in job quality with increases in informality.

Keywords: migration, labor market, unconditional quantile regression, difference in differences model, multinomial logit.

Resumen

El objetivo es presentar evidencia empírica sobre el impacto de la migración en salarios y empleo del mercado de trabajo de Colombia, a través de la estimación de un modelo de regresión logística tipo logit multinomial para el empleo y una regresión cuantílica incondicional para el efecto en los salarios, con información de 2015 a 2019. Para ambas estimaciones se emplea un modelo diferencia en diferencias para determinar el efecto de la migración. La principal conclusión del estudio señala evidencia de un efecto sobre la distribución de empleo y salarios que afecta a los grupos más vulnerables, con menor educación e informalidad, a través de un incremento de la competencia en el segmento de mano de obra no calificada. El efecto sobre los salarios es limitado, pero mucho

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* Corresponding author: Jacobo Alberto Campo Robledo. E-mail: jacampo@ucatolica.edu.co

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más evidente en los cuartiles de ingresos más bajos de la distribución de ingresos, con una significativa caída en la calidad del empleo con incrementos en la informalidad.

Palabras clave: migración, mercado laboral, regresión cuantílica incondicional, modelo diferencia en diferencias, logit multinomial.

Introduction

According to the International Labor Organization (OIT, 2018), immigration caused by economic, social, and political problems exceeded 272 million people worldwide before the arrival of the COVID-19 pandemic. According to the United Nations Refugee Agency (2023), the migration crisis from Venezuela in Latin America is registered as the largest in the last 50 years, and according to the World Bank (Banco Mundial, 2018), due to its intensity and speed, it is considered one of the highest migrations on record. The particular case of Venezuela stands out in recent experiences of forced, rapid and mass migration, a consequence of growing poverty, unemployment, hyperinflation and a political crisis characterized by a general distrust in institutions in an environment of falling international oil prices.

The above has driven a mass migration of Venezuelan citizens to border regions of Colombia. According to the United Nations High Commissioner for Refugees (Alto Comisionado de las Naciones Unidas para los Refugiados, 2024), Colombia has been the largest recipient of the migration flow from Venezuela compared to other countries in the region. According to the National Administrative Department of Statistics (DANE), by 2019, 1 717 352 Venezuelan citizens had entered the country, 19% between 18 and 29 years old and 11% between 30 and 39 years old. This population was mainly located in Bogota (19.43%), Norte de Santander (11.5%), Atlántico (9.24%), and Antioquia (8.98%). The mass arrival of migrants from Venezuela occurred in the context of a labor market participation of the native population estimated at 63% from 2016 to 2019. At the same time, the labor market participation of the migrant population stood at 66%, characterized by high levels of informal employment and low-quality jobs (DANE, 2019).

In addition to the higher labor participation of the migrant population compared to the native population, the unemployment level decreased in Venezuela, while it barely changed in Colombia. The decrease in the unemployment level in Venezuela is associated with the outflow of people (Instituto Nacional de Estadística, 2019), while labor participation levels in Colombia increased, which increased the unemployment rate that was on an upward trend even before the arrival of the migration flow in the period from 2016 to 2019.

Adjustments in the labor market as a result of labor supply mobility also had an impact on employment. In the same period, the employment rate in Venezuela and Colombia maintained similar shares at 56% and 59%, respectively. Despite the apparent similarity in the indicator, the level of employment was more volatile in Colombia compared to Venezuela. The arrival of the labor force from Venezuela increased the labor supply in segments with greater accessibility and lower access barriers, which increased competition between native workers and migrant workers, with possible impacts on wages. This exacerbated labor market failures associated with informal employment, limited social protection, and deficits in labor rights, which generated the need for public policy reforms to take advantage of the economic opportunities associated with migration flows (Instituto Nacional de Estadística, 2019).

The size of the migration flow has revolved around the opportunities that metropolitan labor markets in Colombia provide for newcomers. In particular, the unemployment rate of the Venezuelan migrant population in Bogota (11.2%), Barranquilla (16.5%) and Cúcuta (22.7%) increased relative to other urban centers as a result of the presence of a higher level of migrants. Bogota presented a decrease in unemployment from 21% to 11% between July 2019 and September 2020. Likewise, when comparing the unemployment rate of migrants with the unemployment rate in Venezuela one year ago, labor market conditions are similar, with a difference of one percentage point below the situation in Venezuela.

Although labor market conditions are not very different for the migrant population when comparing the state of the labor market in Venezuela with the labor market in Colombia, there are differences between the long-term migrant population and the short-term migrant population. According to a report issued by DANE (2019), the unemployment rate for the short-term or recent migrant population of 20.7% is five percentage points above the long-term migrant population. Meanwhile, labor participation does not present significant differences between the two groups. The above indicates the most outstanding characteristic of the recent migration flow related to a mass and rapid movement occurring in a short period, with direct implications for labor participation.

Considering the significance of the recent increase in migrant labor participation, this paper presents the results of estimating a difference-in-differences model to understand the impacts of migration on the labor market in Colombia. This contributes to the recent literature on diagnostic exercises conducted by multilateral entities such as the World Bank (Banco Mundial, 2018) and the Colombian government (Departamento Nacional de Planeación, 2014, 2018) and in the scientific literature. Notably, the results of recent studies have pointed to an increase in the size of the informal economy, an increase in underemployment, and consequent downward pressures on the wages of native workers in the unskilled labor segment of the labor market. From the academic perspective, particularly in the recent research by Caruso et al. (2021), an adverse impact of migration on the wages of native workers is noted, especially in the informal segment.

Based on the state of the art and considering the review of specialized literature on the measurement of migration impacts in Colombia, the research contributes in at least three aspects to the current debate on the effects of migration. First, the study performs a disaggregated analysis of the incidence of migration on the labor market, identifying that the greatest effect is concentrated in the informal sector—which accentuates the relevance of demographic characteristics such as age, gender, marital status and work experience in the distribution of wages and employment in the formal and informal segments of the labor market in Colombia—through a microeconometric emphasis that establishes transmission mechanisms of the labor supply shock toward the results observed in the labor market. Second, unlike other studies conducted to measure the impact of forced migration on the native labor market in Colombia, the use of econometric models to explain the effect of changes in employment and wage distributions facilitates the understanding of the effects of the rapid and mass arrival of migrants, which influences the design of adjustment programs in the labor market. Third, the empirical evidence provided reinforces the idea that migration interacts with other vulnerabilities, creating scenarios of greater disadvantage for certain groups, in addition to the effect of migration on the informal sector.

To this end, the study offers a rigorous and differentiated technical analysis of the impact of migration on the labor market. It highlights the importance of considering labor segmentation, the socioeconomic characteristics of migrants, and the interactions between different types of vulnerability. The main conclusion suggests evidence of an effect on the distribution of employment and wages affecting the most vulnerable groups, with lower education levels and in informal employment, through increased competition in the unskilled labor segment. The effect on wages is limited, albeit much more evident in the lower income quartiles of the income distribution, with a significant drop in employment quality with increasing informal employment. The research agenda that emerges from the results suggests the relevance of exploring the impacts of labor migration within the migrant population, comparing outcomes in wages and labor participation among long-term immigrants, short-term immigrants, Colombian returnees and native workers.

The paper is organized into six sections, beginning with an introduction. The second section discusses the state of the art in the measurement of the effects of migration on the labor market. The third section explains the data and the methodological basis of the econometric estimations, places special emphasis on a measurement of changes in the distributions of jobs and wages and identifies transmission mechanisms based on the demographic conditions of native workers and migrant workers. Section four presents the results of the estimations. The results are discussed in the fifth section, and the last section presents a conclusion.

Review of the literature

The effect of migration on labor markets has been widely explored in the specialized literature due to the consequences for labor productivity, employment and wages of the native worker population (Becker & Ferrara, 2019; Dustmann et al., 2016; Maystadt et al., 2019). The design of adjustment programs implemented by the governments of receiving countries requires knowledge and understanding of the transmission mechanisms of labor migration to stop the negative effects and enhance the positive effects on vulnerable workers by educational level and work experience of the native population (Tumen, 2015). In addition to the above, the indirect effects of migration on consumption, prices, taxation and policy preferences have been particularly discussed in the specialized literature as relevant aspects of establishing a comprehensive framework of analysis of the consequences of migration for economies and policy outcomes in host countries (Becker & Ferrara, 2019).

In the specialized literature it is possible to identify two groups of research related to the effect of migration on the labor market in host countries. In a first group, research related to the effect of voluntary migration on the native labor market is found (Aydemir & Borjas, 2007; Borjas, 2003, 2014; Hoang, 2020; Instituto de Estudios y Divulgación sobre Migración, 2015; Janta et al., 2011; Lee et al., 2020; Llull, 2018; Lozej, 2019; Ottaviano & Peri, 2012; Shi et al., 2007, 2011; Wu et al., 2020); and in a second group, research concerning involuntary migration (Abuelafia & Saboin, 2020; Altonji & Card, 2019; Azlor et al., 2020; Bağır, 2018; Balkan & Tumen, 2016; Bonilla-Mejía et al., 2020; Card, 1990; Caruso et al., 2021; Cárdenas & Mejía, 2006; Ceritoglu et al., 2017; Esen & Binatli, 2017; Fallah et al., 2019; Maguid, 1986; Mora et al., 2023; Morales & Pierola, 2020; Olivieri et al., 2022; Pedrazzi & Peñaloza-Pacheco, 2021; Peñaloza-Pacheco, 2022; Vargas Ribas, 2018; Rodríguez Vignoli, 2017; Santamaria, 2022; Sassen, 2015; Stefoni, 2018; Tribín-Uribe et al., 2020).

A notable difference between both groups is related to the nature and causes of migration. While the first group focuses on migration with the ability to choose the labor market regarding occupations and places of preference, the second group establishes the effect of rapid and mass migration without the possibility of choosing occupations and destinations. Nevertheless, both groups of research seek to establish the degree of substitution and complementarity of migrant workers and native workers.

The evidence suggested by the first group of research points to inconclusive results on substituting native workers with migrant workers. According to Dustmann et al. (2016) it is possible to identify three different approaches to measuring the effect on the native labor market of voluntary migration. In the first approach, changes in labor demand are estimated by matching native workers and migrant workers according to their educational level and work experience. The second approximation considers the possibility of migrant labor market mobility by estimating the effect of migration on the regional or national labor market. Finally, the third approach emphasizes the importance of simultaneously controlling for the characteristics of education and work experience and the mobility of migrant workers in the host labor market.

Using an economic model structured on a production function, the three approaches examine the effect of voluntary migration on labor productivity to determine the degree of complementarity or substitution of native labor by migrant labor. Econometric identification uses instrumental variable models to correct the endogeneity bias caused by the choice of occupations and place of participation in voluntary migration. Estimates are frequently made with population census data that include data on native workers and first- and second-generation migrants.

Due to the different approaches—which differ in terms of skills, labor market participation and migrant mobility—the comparison of results on the estimated effect is limited, so the evidence on substitution effects is inconclusive on negative effects on wages and employment of native workers because some studies do not reject negative effects, while other studies reject substitution effects (Aydemir & Borjas, 2007; Borjas, 2014; Card & Peri, 2016; Llull, 2018; Ottaviano & Peri, 2012).

On the other hand, the more recent literature on the effects of forced migration on the native labor market can be organized into two groups. One group includes research on the effects of forced migration from Syria to Turkey and Jordan. The other group includes research on the effect of migration from Venezuela to Colombia, Ecuador and Peru. The evidence suggested by research in the first group points to short-term effects on the size of informal employment and displacement of less skilled informal workers, particularly native workers as well as migrant workers who were working in the host countries before the arrival of the rapid and mass forced migration flow (Bağır, 2018; Balkan & Tumen, 2016; Esen & Binatli, 2017; Fallah et al., 2019).

For the second group, particularly in Colombia, the results suggest increases in work hours (Mora et al., 2023) and null effects of work permit policies for migrants on native employment (Santamaria, 2022). Other research shows heterogeneous effects with negative impacts on the participation of young people, men and women in informal employment with unskilled labor and positive impacts for women with skilled labor (Pedrazzi & Peñaloza-Pacheco, 2021; Peñaloza-Pacheco, 2022).

Regarding the effects on wages, the evidence is not conclusive. On the one hand, some studies report null effects on wages (Mora et al., 2023; Santamaria, 2022), both in the informal and formal labor markets. On the other hand, other studies find negative effects, particularly for informal native workers (Caruso et al., 2021; Peñaloza-Pacheco, 2022). In the case of Peru (Morales & Pierola, 2020), evidence suggests impacts on the probability of native workers with tertiary education to be employed informally in sectors other than the service sector and a decrease in the monthly income of workers with secondary education and a formal job in the service sector. For the case of Ecuador (Olivieri et al., 2022), the reported findings imply a negative impact on women's labor participation and a decrease in the quality of youth employment due to increased informal employment.

The evidence suggested for the case of forced migration does not use economic models structured around a production function that focuses on the effects on employment and wages in the short run. The research design uses the framework of econometric difference-in-differences models using instrumental variables. Likewise, the data sources used refer to household surveys, administrative records of the migration flow and instrumental variable estimates using the initial set of immigrants (Peñaloza-Pacheco, 2022), demographic characteristics such as the distance in kilometers to the border, the temperature in the municipalities of departure and arrival of the migration flow (Mora et al., 2023) and Internet searches (Santamaria, 2022).

One of the advantages of forced migration studies, compared to voluntary migration studies, concerns the exogeneity of the migration flow insofar as migrants do not decide on the occupations or the place in which they participate in the host labor market, which facilitates the identification of the causality parameter in econometric estimations (Tumen, 2015). Despite the above, estimates of the effect of migration on employment and wages in the framework of a difference-in-differences econometric model are not without limitations. These limitations correspond in part to the learning achieved in the estimations of the long-run effect.

Longer-term spillover effects, such as the outflow of native workers from migrant arrival sites, the arrival of firms seeking migrant workers in areas with the highest concentration of migrants and the upgrading of migrants' education to participate in the host country's labor market affect the distribution of native workers, the occupations available in the host labor market and the competition in the sites with the highest concentration of native workers.

Likewise, the heterogeneous effects on young people, men and women depend on the skill distribution of the migrant worker population (Pedrazzi & Peñaloza-Pacheco, 2021). Finally, the selection of the control group—from which the counterfactual of native workers affected by the migration flow is established—has an impact on the results reported in the forced migration literature, which has led to the implementation of sensitivity exercises in the estimations with alternative control groups (Mora et al., 2023; Pedrazzi & Peñaloza-Pacheco, 2021) and the estimation of contrast tests using bootstrapping methods (Roodman et al., 2019).

This research contributes to the evidence reported on the effects of forced migration from Venezuela to Colombia on the probability of native workers finding formal and informal employment and the distribution of wages in the Colombian labor market. The study's main conclusion points to evidence of an effect on the distribution of employment and wages that affects the most vulnerable, less educated and informal groups through increased competition in the unskilled labor segment.

The effect on wages is limited but much more evident in the lower income quartiles of the income distribution, with a significant drop in employment quality with increases in informal employment. Therefore, the findings of this paper confirm the reported limited or null effects on wages (Mora et al., 2023; Santamaria, 2022) and advance in the estimation of the effects on the distribution of formal and informal employment and the distribution of wages.

Limitations related to the identification of the parameter measuring the effect of forced migration on the quartiles of employment and wage distribution have been pointed out in the specialized literature (Callaway et al., 2018; Fan & Yu, 2012; Roodman et al., 2019). Specifically, identifying and estimating the effect of a treatment on the quartiles of a distribution requires the use of additional assumptions because it is affected by an unknown dependence between the change in potential untreated characteristics and the initial level of those same characteristics for each group in the wage and employment distribution. To solve the problem of identifying the parameter of interest, the specialized literature proposes using a new assumption required to estimate the effect on the quartiles of a distribution called the stability assumption. According to this assumption, the unobserved dependence remains constant over time, which facilitates the identification and estimation of the effect on the quartiles of the distribution of employment and wages.

The following section on methodology describes the identification of the effect on the distribution, including the stability assumption, by specifying the scope of the findings reported in this research.

Data and methodology

Considering the above, this paper estimates the effects of the migration flow based on the accumulated scientific evidence and tests the hypothesis according to which the migration flow is exposed to low-quality jobs with impacts on the distribution of wages. The sources of information used and the methodological design proposed to investigate the research hypothesis identified in the state of the art on the effects of a rapid and mass migration flow on the labor market are discussed below.

The analysis period was from 2015 to 2019, where the impact of a natural migration explosion in the country between 2016 and 2018 was measured, so there are two comparison groups, one before and the other after the mass migration. The data come from the Gran Encuesta Integrada de Hogares (Major Integrated Household Survey) of the National Administrative Department of Statistics (DANE, Spanish acronym of Departamento Administrativo Nacional de Estadística), where the socioeconomic characteristics of the people interviewed, migrants and non-migrants and the regions or areas with greater migration, as well as their employment and salary indicators, are observed. Table 1 describes the variables used in the analysis. It is worth mentioning that these variables are standard in studies on the effects of migration. The choice of these variables is based on the existing empirical evidence on the factors that influence migration flows.

Table 1. Description of variables

Variable	Description
ln_inglab	Dependent variable in quantile models. It is the logarithm of the average monthly labor income
Formal, informal, unemployed	Dependent variable in the multinomial logit
Migra_pressure	1 are the regions with the highest migration pressure, and 0 are the regions with the lowest migration pressure
Time	1 is the year 2019, and 0 is the year 2015
Time_pressure	The multiplication of the *migra_pressure* variable by time
Educational level	1 no formal educational qualification, 2 if high school graduate, 3 if a technical degree, 4 if a university graduate, 5 if a postgraduate
Sex	1 if male and 0 if female
Young people	1 if age is between 18 and 28 years old
Head of household	1 if head of household and 0 for others
Marital status	1 if married or in a domestic partnership and 0 for others

Source: created by the authors

The methodology of this study is based on the use of a difference-in-differences model to measure the change or impact of the migration of the Venezuelan population on employability and income in Colombia, supported by two complementary measurement methodologies: a *multinomial logit* regression model for employment and an *unconditional quantile regression* for the effect on wages.

The choice of the multinomial logit model in this study is based on its statistical and interpretative advantages. The coefficients of this model are interpreted as changes in the odds ratio of belonging to a specific category of the dependent outcome (type of employment: formal, informal, unemployed) compared to the reference category. This interpretation is more intuitive and communicable than that of the *multinomial probit*. Furthermore, the multinomial logit assumes a logistic distribution of the error, which is appropriate especially when the dependent variable is categorical with more than two categories. The coefficients are interpreted as changes in the logarithm of the odds ratio between two outcome categories. Finally, this model does not require the error variance to be constant at all outcome levels, which is useful in the presence of biased values, such as employment and unemployment rates in categorical variables.

The multinomial probit could also be considered, especially if the logistic distribution of the error is in doubt. Nonetheless, it assumes a normal distribution of the error, which may be more appropriate in cases where the data distribution is not biased, requiring a constant variance of the error at all levels of the result.

The choice of quantile regression is justified by its ability to estimate the effects of migration at different points in the wage distribution. This ability is crucial for understanding how migration affects different income groups within the labor market, especially in income distributions not following a normal distribution. Moreover, quantile regression is less sensitive to outliers in the data, making it more suitable for analyzing income distributions that may have such observations. It provides additional information on the shape of the wage distribution, which facilitates the identification of possible changes in wage inequality associated with migration.

Compared to other alternatives such as linear regression, which assumes a normal distribution of error and is not suitable for wage distributions, and models such as weighted least squares (WLS) or Poisson regression, quantile regression offers a combination of advantages that make it the most appropriate choice for this case, especially in the face of more atypical data distributions.

Finally, although there are models such as the Oaxaca-Blinder model (Blinder, 1973; Oaxaca, 1973) that could address the distribution of the data to analyze wage gaps in the style of Rodríguez Pérez and Valdés Martínez (2022), they are not relevant for this study that seeks to identify determinants of the wage distribution and wage increases by each quantile in a specific way. Nonetheless, a similar approach could be achieved by using interquantile models to complement the quantile analysis.

There is a framework of experimental methodologies in the economic literature that are not easy to carry out for different reasons of implementation and data access costs. Nevertheless, there are quasi-experiments in which, by chance, effects are generated that are considered natural and, therefore, generate an assignment between the treatment group ($D = 1$) and the control group ($D = 0$) that can be compared over time.

Similarly, using individual data should be the same in both periods, although comparing this is not always possible when the phenomenon occurred before measuring the impact. The latter is especially important in the use of microdata from household surveys, which are the easiest to access and use for the desired measurement of the impact of migration on the labor market since the difference-in-differences model in the presence of these fortuitous events can observe a treatment assignment very close to randomization and allows existing differences between the treatment group and the control group to be observed, which must be corrected to avoid biases.

As Bernal and Peña (2017) stated, the difference-in-differences model evaluates the expected change in Y between the period after $(t = 2)$ and the period before mass migration $(D = 1)$ at the time it occurs $(t = 1)$, minus the expected difference in employment in the control group $(D = 0)$ during the same period. Accordingly, the required information is presented in Table 2.

Table 2. Difference-in-differences model information

	Treatment	**Control**
$t = 1$ (baseline)	$Y1 \vert D = 1$	$Y1 \vert D = 0$
$t = 2$ (follow-up)	$Y2 \vert D = 2$	$Y2 \vert D = 0$

Source: Bernal and Peña (2017)

In the case study, there may be systematic differences between the treatment group in areas with higher migrant rates and the control group in areas with lower migrant numbers before mass migration, which would be a treatment effect. It is therefore important to observe these differences to estimate the real effect of migration on the *result* variable since the difference between the treatment group and the control group in the period after mass migration would be associated with the treatment itself and the differences before mass migration. This is one of the great advantages of the difference-in-differences model since it controls for these possible differences existing in the two groups, which allows for an unbiased estimation.

Thus, the impact of the phenomenon by the difference-in-differences method is given by:

$$\tau = \left[E\left(Y_2 \middle| D = 1 \right) - E\left(Y_1 \middle| D = 1 \right) \right] - \left[E\left(Y_2 \middle| D = 0 \right) - E\left(Y_1 \middle| D = 0 \right) \right] \quad (1)$$

And its estimator is given by:

$$\hat{\tau} = \left[E\left(\overline{Y}_2 \middle| D = 1 \right) - E\left(\overline{Y}_1 \middle| D = 1 \right) \right] - \left[E\left(\overline{Y}_2 \middle| D = 0 \right) - E\left(\overline{Y}_1 \middle| D = 0 \right) \right] \quad (2)$$

With $\left(\bar{Y}_t \middle| D=1\right)$ being the sample average of Y in period t in the treatment group and $\left(\bar{Y}_t \middle| D=0\right)$ the sample average of Y in period t in the control group. The estimator can be represented $\left(\hat{\tau}\right)$ as

$$\hat{\tau} = \left(\Delta Y \middle| D=1\right) - \left(\Delta Y \middle| D=0\right) \qquad (3)$$

Where,
$\left(\Delta Y \middle| D=1\right)$ measures the average change in Y between period 2 and period 1 in the treatment group; $\left(\Delta Y \middle| D=0\right)$ measures the average change in Y between period 2 and period 1 in the control group. This estimator is unbiased and efficient if it meets the randomization assumption, that is, if the treatment has been randomly assigned.

To gain efficiency in the estimator of the effect of mass migration, the determinants and their persistence over time are observed as control variables that make people similar to each other, such as sex, schooling, being head of household and age. Eliminating the existing differences between the two groups and ensuring that the treatment group is not related to an initial level of employability and wages at baseline will allow the estimator to be unbiased as long as the assumption of parallel trends exists, which occurs because the difference-in-differences model generates a random assignment but is not randomly perfect. This occurs when the differences between the treatment and control groups are a time trend of the employment and wages variable as a difference between the two periods, and this variable is the same in both the treatment and control groups, that is, the outcome variable evolves naturally over time in the same way as the two groups. So, in this case, there is a parallel trend.

Furthermore, by including unobserved variables—which in some way can explain pre-existing differences between the groups, commonly known as control variables—the effect of changes due to migration, controlled by changes in the possible variables that generate differences between the groups, can be measured over time. By including these variables, the estimator's efficiency improves, parallel trends are fulfilled and the estimator can be adjusted for observable characteristics.

Given the nature of the Colombian household survey—where there is a series of repeated cross-sectional data, where each stage corresponds to a period—it is necessary to control for the variables described above. The difference-in-differences model allows this to be done to overcome the problem of not having panel data to observe the same individual over time. With this, the individuals of the initial cross-sectional database can be used as substitutes for the individuals of the treatment group, the control group and the subsequent cross-sectional group, that is, using groups that are not equal but similar in an initial period and in a period after the mass migration of Venezuelans. For this, it is necessary to be able to identify the units belonging to a treatment group where the use of control variables of regions can be useful, and it is required that the composition in terms of unobservable variables of those who will be in the treatment group and in the control group remains constant. That is, the unobserved variables of

Venezuelan migrants in 2015 should be the same as the observed variables of migrants in 2019 so that individuals from 2015 can be used as proxies for individuals in the treatment group and those in the 2019 control group.

$$Y_i = \alpha_0 + \alpha_1 D_i + \alpha_2 X\left(t=2\right) + \alpha_3 D_i X\left(t=2\right) + \varepsilon_{it} \quad (4)$$

Where
D_i is equal to 1 if the observation corresponds to an individual in the treatment group and 0 to the control group.
$X\left(\cdot\right)$ is an indicator equal to 1 if the condition (.) is met and 0 if not.
$X\left(t=2\right)$ is equal to 1 if the observation corresponds to the follow-up and 0 otherwise.

The term $D_i X\left(t=2\right)$ is the interaction between the treatment indicator D_i and the follow-up period binary variable $X\left(t=2\right)$.

Similarly, the treatment and control variable has been defined by the migration pressure, according to DANE (2022), where the departments with the highest migration pressure above the national average were taken, which shows an inhomogeneous distribution in the limits of the average, so there are notable differences in the rate of migrants per inhabitants in order to better differentiate the departments with the highest and the lowest pressure in the country. To reduce the risk of counting migrants in transit, the indicator used was the immigration ratio of those living in Venezuela for more than five years.

Thus, the treatment group consisted of the departments of Bolívar, Cesar, Cundinamarca, Guajira, Norte de Santander, Santander, Magdalena and Sucre; and the control group consisted of the departments of Antioquia, Atlántico, Bogotá Boyacá, Caldas, Caquetá, Cauca, Córdoba, Choco, Huila, Meta, Nariño, Quindío, Risaralda, Tolima and Valle del Cauca.

In the case of this study, multinomial logit probabilistic models are used to measure the variation in the probability of employability (in the formal and informal segments) and quantile regression to measure the impact on the wages of Venezuelan migrants in the Colombian labor market.

The multinomial logit model has been used in data analysis, among others, to predict the probability of several mutually exclusive and exhaustive categories in a dependent variable, in labor market studies, to determine the probability of employability of job seekers, as determined in works on labor market participation, labor segmentation, and to determine the probability of being employed (for example, Castillo-Robayo, 2019; Castillo et al., 2020; Espino & Sauval, 2016; González-Quintero & Daza-Báez, 2015; Paz, 2013; Sánchez Torres, 2015). In these cases, the model helps to observe the probability of occupation and of entering the formal segment of the labor market, so the determination of the dichotomous variable is based on 1 for employed and 0 for unemployed and, similarly, 1 for formally employed and 0 for informally employed (within the employed group).

Thus, the multinomial logit helps observe the probability of employment and of entering the formal labor market segment. It is used to identify job seekers with the highest probability of being employable and to identify the specific characteristics that make them more employable. It can also provide specific recommendations to job seekers to improve their employability based on their characteristics. It is estimated that

$$ML\ (Formal|Informal|Unemployed) = f\begin{pmatrix} Migra\_pressure, Time, Time{*}pressure, Sex, \\ Head\ of\ household, Marital\ estatus, Young\ people \end{pmatrix}$$

Finally, the distribution of labor income and its relation to the variables of interest is measured using the *quantile regression* model. The model of the impact on wages is estimated as proposed by Card (1990), who states that a phenomenon such as mass migration can be taken as a random effect or experiment in the areas where this migration occurs.

In this way, the mass migration to Colombia between 2017 and 2018 toward certain regions is considered a random phenomenon, where the treatment group will be the regions with the highest migration, and the control group will be the regions with no or little migration. For this purpose, data from Migración Colombia were taken showing that around 70% of migration was concentrated in Bogotá, Norte de Santander, Atlántico, Antioquia, Guajira, Santander Cundinamarca, Valle del Cauca, Bolívar, Cesar and Arauca. These departments comprised the treatment group. The control group comprises the rest of the departments with very low percentages of migration, mostly less than 1%; so, for this study, it is assumed that they are not significant in labor changes in these regions.

In the traditional model (ordinary least squares, OLS), errors are taken as a succession $(\quad)$ of random variables that are independent and identically distributed with a mean equal to zero. Nonetheless, the assumption of normality is not always fulfilled since there are asymmetric distributions, so Koenker and Bassett (1978) introduced quantile regressions to solve this asymmetry problem. Their work demonstrated that quantile regression estimators are more efficient.

Another substantial difference is that the classical model aims to minimize the sum of squared errors and relies on the mean for the calculations. In quantile regression, the sum of absolute errors weighted for the effect of asymmetries is minimized, and quantiles are used as estimators.

The quantile regression described below is based on the work of Koenker and Bassett (1978) and Buchinsky (1998) for the methodology, and Buchinsky (1994) and Castillo Robayo et al. (2017) for their emphasis on the determinants of wage differentials. The quantile model can start from a distribution with x elements $x, x^2, \ldots, x^n \in \mathrm{R}^x$ and n real values $z_1, z_2, \ldots z_n$. Where the optimization problem is defined as:

$$\min f(\partial) = \sum_{i=1}^{n} \left(y_i - \partial^T x^i \right)^2 \qquad (5)$$

Likewise, from Equation 5, the following can be obtained:

$$\hat{\partial} = \underset{\varepsilon_T \in \mathrm{R}}{\arg\min} \left\{ \sum_{y_i \geq \varepsilon_T} T \left| y_i - \partial^T x^i \right| + \sum_{y_i < \varepsilon_T} (1 - T) \left| y_i - \partial^T x^i \right| \right\}$$

$$\hat{\partial} = \underset{\varepsilon_T \in \mathrm{R}}{\arg\min} \sum_{i=1}^{n} \rho_T \left(y_i - \partial_t^T x^i \right) \tag{6}$$

$$\hat{\partial} = \underset{\varepsilon_T \in \mathrm{R}}{\arg\min} \sum_{i=1}^{n} \rho_T \left(\varepsilon_i \right)$$

Where T is a value between 0 and 1, $\left(T \in (0,1)\right)$ and ρ_T is the *check function* which can be expressed as

$$\rho_T \left(\varepsilon_T \right) = \begin{cases} T \varepsilon_i, & \textit{if} \quad \varepsilon_i > 0 \\ (1 - T) \varepsilon_i, & \textit{if} \quad \varepsilon_i > 0 \end{cases}$$

In Equation 6, all observations greater than $\hat{\partial}_t^T x^i$ are estimated by $\hat{\partial}_t x$ with weight in T, and in the smaller ones, $\hat{\partial}_t x$ with weight in $(1\text{-}T)$. Also, the observations greater than the absolute value of the difference between the observations and the optimal value are seen, which have a weight of order T, and the smaller observations have a weight of order $(1\text{-}T)$.

Subsequently, the problem of identifying effects on the distribution of workers' labor market outcomes due to a random shock is described. The description of the identification of the quantile effect is done considering the contributions of Callaway and Li (2019) and Fan and Yu (2012). It starts from the question: How does the distribution (wages, employment and informal employment) of native workers change as a consequence of forced migration from Venezuela compared to the change in the distribution (wages, employment and informal employment) of native workers in the absence of forced migration?

To estimate the quantile effect of forced migration, the following criteria are met:

- Access to a data panel for at least three periods for all individuals in a sample $(t, t\text{-}1$ and $t\text{-}2)$.
- The random perturbation is binary treatment.
- No individual in the sample receives treatment before the final period t.

For all individuals who perceive the random disturbance at time (t), $D = 1$, indicating that they belong to the treated group. For all individuals who do not perceive the random disturbance at time (t), $D = 0$, indicating that they belong to the control group.

The research team observes the labor market results of interest Y_t, $Y_{t\text{-}1}$ and $Y_{t\text{-}2}$ for each individual in the sample at each point in time $(t, t\text{ - }1$ and $t\text{ - }2)$. At the same time, the researcher can observe some control variables X.

All individuals belonging to both the control group and the treatment group have potential results associated with them depending on whether they belong to the control group or the treatment group, Y_{1t} y and Y_{0t}.

The core problem implies that only one of the potential results is observed for a particular individual. The observed result can be described from:

$$Y_t = DY_{1t} + (1 - D)\, Y_{0t}$$

Because no individual is treated in periods prior to *t*. To achieve a precise distinction between the potential outcomes of individuals in the control group and in the treatment group, it is indicated that the results Y_{1t} , Y_{0t-1} and Y_{0t-2} are observed results for the treatment group, implying that the result Y_{0t} is not observed for the treatment group, while Y_{0t}, Y_{0t-1} and Y_{0t-2} are observed results for the control group.

Since no individual is treated in periods prior to *t*, the results prior to the labor market shock observed for all individuals belonging to both the control and treatment groups are Y_{0t-1} and Y_{0t-2}. The above implies:

$$Y_{t-1} = Y_{0t-1} \text{ and } Y_{t-2} = Y_{0t-2}$$

For any individual, the unobserved potential result is called the counterfactual. Thus, the counterfactual of individuals in the treatment group is Y_{0t}. Then, the individual effect of exposure to the labor market shock defined from $Y_{1t} - Y_{0t}$ is unobserved because only one of these results is observed for each individual. In the estimation of the average effect using the difference-in-differences method, it is assumed that the unobserved trend of individuals belonging to the treatment group can be replaced with the observed trend of individuals belonging to the control group.

Estimating the effect of the disturbance on the change in the distribution is relevant when: *1*) the effect of the disturbance is heterogeneous across individuals in the sample; and *2*) understanding the heterogeneity is relevant because some quartiles receive a larger or smaller effect compared to other quartiles of the distribution.

Comparing the observed distribution of labor market results with the distribution of a counterfactual provides more information to understand the disturbance's effects compared to the disturbance's average effect. For example, from a public policy design perspective, employment protection programs for young people, women or informal workers require knowledge about the change in the distribution of potential results compared to a counterfactual result of the distribution in the absence of the random disturbance.

According to Callaway and Li (2019), the distribution of a random variable Y for a quartile τ of the distribution of Y is defined from:

$$y_\tau = F_Y^{-1}(\tau) = inf\{y{:}F_Y(y) \geq \tau\}$$

F_Y describes the distribution of Y and y_τ describes the quartile of interest to measure the effect of exposure to the random disturbance on the labor market. Therefore, the quantile effect of exposure to the random disturbance on y_τ can be measured from:

$$ECT(\tau) = (F_{Y1t}^{-1} \mid D = 1 \ (\tau)) - (F_{Y1t}^{-1} \mid D = 0 \ (\tau))$$

Identification under difference-in-differences assumptions assumes that for individuals in the treatment group, the potential result of exposure to the random disturbance (forced migration) and the potential result of not being exposed to the random disturbance are observed in different periods (Y_{t-1}, Y_{t-2}, Y_t). In the group of individuals not exposed to the random disturbance belonging to the control group, the potential result of being exposed to the random disturbance is not observed.

Identification assumption 1: parallel trends

The assumption of parallel trends implies:

$$E(\Delta Y_{0T} \mid D = 1) = E(\Delta Y_{0T} \mid D = 0)$$

On average, the unobserved change in labor market results for the group of individuals exposed to the random disturbance is equal to the observed change in labor market results for the group of individuals not exposed to the random labor market disturbance. Regarding the quantile effect of the disturbance, the parallel trends assumption is strengthened with assumptions 2 and 3 because the quantile effect depends on the full distribution of individuals not exposed to the disturbance, unlike the average effect, which depends on the average value of the distribution.

Identification assumption 2: distributional difference-in-differences assumption in differences

The distributional difference-in-differences assumption holds that the distribution of the change in potential labor market results of individuals in the control group not exposed to the random disturbance does not depend on an individual belonging to the control group or the treatment group. Estimating the average effect implies that the unobserved trend of individuals in the treatment group can be replaced with the observed trend of individuals in the control group. By the same reasoning, the estimation of the quantile effect assumes that the unobserved trend of the distribution of individuals belonging to the treatment group can be replaced by the observed trend of the distribution of individuals belonging to the control group.

Identification assumption 3: dependence between change in distribution and initial values of the distribution

Because assumption 2 is not sufficient to identify the quantile effect, even if the sum of the distributions of the results of treated and untreated individuals with known marginal distributions is known, the inclusion of a new assumption is required to identify the estimator of the quantile effect.

Assumption 3 implies that the dependence between the change in the distribution of labor market results of individuals not exposed to the random disturbance (used to replace the unobserved distribution of individuals exposed to the random disturbance) and the initial values of the distribution of labor market results for individuals not exposed to the random disturbance is stable over time.

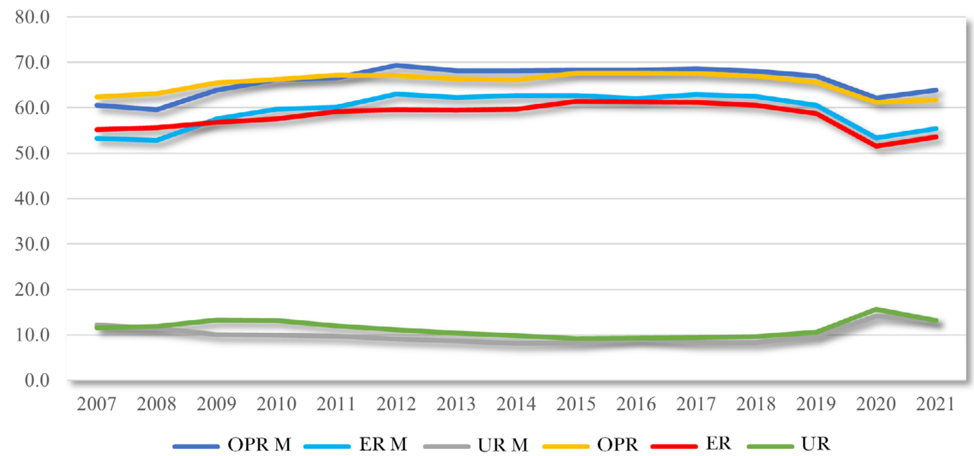
Therefore, if in the past the increases or decreases in labor market results tend to be located in the highest quartiles of the distribution, then in the present, the increases or decreases in labor market results tend to be located in the highest quartiles of the distribution. In other words, individuals who in the past had the highest increases or decreases tend to perceive in the present the highest increases or decreases over the initial distribution. For example, in the case of wages, if in the past quartile 4 had the highest increases in the wage distribution, then in the present quartile 4 tends to have the highest increases in the wage distribution.

Assumption 3, required to identify the distributional effects of forced migration, does not imply restrictions on the distribution of the change in the labor market results of interest over time nor a restriction on the distribution of the change in past labor market results. Instead, it imposes a restriction on the dependence between the distribution of the random variable of past results and the distribution of the random variable of present results of untreated results, which is assumed constant in order to identify the quantile estimator of the effect of the random disturbance of migration on the labor market results of the population exposed to that disturbance.

Results

For the difference-in-differences model, the groups with greater migration pressure were compared to those with less migration pressure. For this exercise, the parallel trends of the main labor indicators in the two groups were compared first. Thus, each indicator is averaged and compared over time. The results in Figure 1 reveal that, in the unemployment rate, overall participation rate, and employment rate, the average of the departments does not show a difference in the trend. Moreover, the average indicators are very similar between the two groups, so it is possible to compare the effects of migration pressure in the periods in question using the difference-in-differences method.

Figure 1. Parallel trends



Note: OPR M: Overall participation rate of the migrant population. ER M: Employment rate of the migrant population. UR M: Unemployment rate of the migrant population. OPR: Overall participation rate of the native population. ER: Employment rate of the native population. UR: Unemployment rate of the native population.
Source: created by the authors based on data from DANE

Considering the above, Table 3 shows the results of the difference-in-differences model through the multinomial logit model that makes it possible to evaluate the effect of migration on employment and the quality of occupations in the country (measured in terms of sectoral formality). There, it is observed that the variable that adds the regions with greater migration pressure (migra_pressure) increases the probability of being in an informal job and decreases the probability of being in a formal job and of being unemployed. The time variable decreases the probability of being in formal and informal employment and increases the probability of unemployment. The time_pressure variable shows that the probability of being in informal jobs and being unemployed increased, but the probability of being in formal jobs decreased.

These three variables, especially the migra_pressure variable, are the ones that show the impact. In this case, the regions with higher migration pressure in the two periods show a positive variation in the probability toward informal jobs, indicating that the occupation is focused on more precarious jobs in these areas. The time variable shows a general deterioration of the labor market since comparing 2019 with 2015 shows that there is a positive variation in the probability of being unemployed and a negative one in any form of occupation (formal and informal), indicating that, in general, employment falls over time.

On the other hand, the variable that takes the effect of the treatment group and time (time_pressure) shows that the impact of migration of people from Venezuela in the areas of interest was negative in formal jobs and positive in informal jobs and unemployment. This indicates that there is indeed a negative impact on the labor market in the regions with greater migration pressure, but this is especially true for informal employment. Nevertheless, there is a significant drop in the probability of being employed in formal jobs or being unemployed.

This does not indicate that national employees are replaced by foreigners because, in the informal segment, there is practically no limit to the generation of employment as many of these jobs are self-employment cases, such as sales on the street or in public transportation. Therefore, there is no conclusion of a decrease in employment due to the substitution of foreign employment. Nonetheless, there is a greater precariousness of employment in these areas and a significant drop in formal jobs, increasing informal employees' vulnerability.

Table 3 also shows that being male increases the probability of being employed compared to being female, but mostly in informal jobs, which gives men a certain advantage in terms of employability but not in terms of labor formality. Heads of household have an increased probability of being in formal jobs and of being employed compared to those who are not, which is explained because they must go out to look for resources for the household and because they may have greater human capital characteristics or advantages in terms of labor participation within the household.

On the other hand, those who are married or in a union have an increased probability of being employed in formal and informal jobs, which is also explained by the behavior of other variables, such as the level of education in the households and the need to find jobs. Young people have a lower probability of being employed in formal and informal jobs than adults, which shows that young people have problems with labor market integration and precariousness.

Education shows that higher educational levels (except postgraduate) decrease the probability of being employed (increase the probability of being unemployed) but increase the probability of doing so in the formal segment. This is explained because more educated people have reservation wages and higher expectations of jobs, so they wait longer in the job search to become employed in formal jobs, as explained by Castillo et al. (2020) and Da Silva Bichara et al. (2022).

As for wages, Table 4 shows the results of the difference-in-differences model with a quantile model, which reflects the results for each quantile distribution group and the effect of migration on them. The analysis was done in both the formal and informal segments to discriminate the participation of each group and its effect on the wages of low-quality or better-quality jobs.

The control variables show the same trend in all quartiles. The *sex* variable shows a positive and statistically significant value in all formal and informal employment quartiles, indicating that being male increases wages compared to being female. The greatest effect in formal employment is in the lowest quartiles and decreases until the 90th quartile, where it increases again, indicating that in the extreme distributions, the effect is greater than in the average distributions. Therefore, it is in the groups with the lowest and highest incomes where, on average, men earn higher wages. In the informal segment, the largest difference is in the middle part (quartiles 25 to 50), falling in the 75th and rising in the 90th, so there is no marked trend in the wage difference between men and women in the formal segment. Beyond the notable wage difference in all groups, there is a difference in all segments that benefits men.

Table 3. Probability of occupation and formal employment, migrants (2015-2019); multinomial logit model

Variables	Formal employment		Informal employment		Unemployment	
	dy/dx	*P > z*	*dy/dx*	*P > z*	*dy/dx*	*P > z*
Migra_pressure	-0.0503	0.0000	0.0577	0.0000	-0.0074	0.0000
Time	-0.0057	0.0000	-0.0131	0.0000	0.0188	0.0000
Time_pressure	-0.0140	0.0000	0.0069	0.0030	0.0071	0.0000
Sex	0.0000	0.9790	0.0420	0.0000	-0.0420	0.0000
Young people	-0.0042	0.0010	-0.0568	0.0000	0.0611	0.0000
Head of household	0.0481	0.0000	0.0077	0.0000	-0.0558	0.0000
Marital status	0.0039	0.0000	0.0295	0.0000	-0.0335	0.0000
Educational level						
Secondary School	0.1822	0.0000	-0.1951	0.0000	0.0129	0.0000
Technical level	0.3561	0.0000	-0.3705	0.0000	0.0143	0.0000
University level	0.5923	0.0000	-0.6104	0.0000	0.0181	0.0000
Postgraduate level	0.6842	0.0000	-0.6469	0.0000	-0.0373	0.0000
Number of obs	=	728141.00				
Wald chi2(22)	=	131851.56				
Prob > chi2	=	0.0000				
Pseudo R2	=	0.1391				
Log pseudolikelihood	=	-606186.10				

Source: created by the authors based on the marginal results of the models

The *head of household* variable positively affects both formal and informal employment. Nonetheless, the effect is more pronounced in the informal segment, where being head of household may represent an obligation to look for a job and to be employed, even if it is precarious, so it would be more common in low-income households, as opposed to formal employment where several people in a household may spend more time looking for a job to work in jobs with better conditions. On the other hand, the *marital status* variable shows positive effects in formal employment but negative effects in informal employment in quartiles 10 and 25, so being married or in a union negatively affects wages in the lower part of the distribution.

In addition, the *educational level* variable shows that wages increase as the level of education increases, which is true in both segments of the labor market. Nevertheless, there is a marked difference in university and postgraduate education with the other levels in the informal segment and it is an effect that deepens as the quartiles increase. A similar effect occurs in the formal segment, where there is a less marked difference between educational levels, but it is a gap that increases considerably in the 75th and 90th quartiles. This indicates that education is a key factor in the wage gap.

The *young people* variable shows that being young has a negative impact on wages in formal and informal jobs in all quartiles, which leads to an income gap for young people.

Table 4. Wages, unconditional quantile model, difference-in-differences, 2015-2019

VARIABLE	Quantile 10		Quantile 25		Quantile 50		Quantile 75		Quantile 90	
	Formal	Informal	Formal	Informal	Formal	Informal	Formal	Informal	Formal	Informal
Migra_pressure	-0.1555	0.0975	0.0213	0.0415	0.0044	0.0253	-0.0095	0.0184	-0.0423	0.0078
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2140
Time	0.2116	0.2773	0.4665	0.1115	0.1667	0.1300	0.1205	0.1989	0.1487	0.1170
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Time_pressure	-0.0800	-0.1665	-0.1080	-0.0702	-0.0675	-0.0980	-0.0556	-0.1181	-0.0599	-0.1432
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sex	0.8448	1.4402	0.2433	0.5261	0.1563	0.4657	0.1743	0.2612	0.1847	0.3296
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Head of household	0.1516	0.4277	0.0740	0.1527	0.0797	0.1558	0.1402	0.1168	0.1966	0.2117
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Marital status	0.1771	-0.1532	0.0569	0.0061	0.0487	0.0753	0.0821	0.0705	0.1034	0.1345
	0.0000	0.0000	0.0000	0.0450	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Young people	-0.2740	-0.2692	-0.1092	-0.0968	-0.1047	-0.1014	-0.1590	-0.0953	-0.1471	-0.1953
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Educational level										
Secondary School	1.0335	0.3911	0.2749	0.1797	0.1616	0.2321	0.1597	0.1686	0.0881	0.2788
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Technical level	1.5611	0.6426	0.5092	0.2859	0.3849	0.3729	0.4161	0.2850	0.2133	0.5325
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
University level	1.3148	1.3012	0.6006	0.5861	0.6562	0.8146	1.2058	0.7027	1.1002	1.7550
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Postgraduate level	1.6558	1.1096	0.7304	0.5390	0.8101	0.8326	1.9142	0.8449	3.2220	2.9770
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Constant	11.6196	10.4662	12.7344	12.1082	13.2369	12.7105	13.5276	13.2472	13.9985	13.4493
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: P-Value between ().
Source: created by the authors based on the results of the models

The *migra_pressure* variable shows the effect of migration on wages in regions with high migration pressure and regions with lower migration pressure. Nevertheless, the net effect is observed with the difference between the groups by year and intra-group for each period, as shown in Table 5, where the coefficients of the variations by year and by quartile determined in the formal and informal segments are shown. It is observed in all quartiles that the *migra_pressure* variable has a negative effect on income, that is, wages in regions with higher migration pressure show an average decrease in income compared to regions with low migration pressure. Nonetheless, the three changes must be observed to determine the true effect.

These variations are observed in the "Difference" column in Table 5, where the coefficients of income variations between 2015 (pre) and 2019 (post) are found. In this case, in formal and informal employment, it is observed that both have negative effects, so there is an unfavorable wage variation in general terms, with greater effect on informal jobs in the lowest and highest part of the distribution (quartiles 10 and 90), which shows greater wage pressures in the most precarious jobs and those with greater stability.

Table 5. Effect difference in migration on wages; unconditional quantile model 2016-2019

		Formal			Informal		
Q10	**Group**	***pre***	***post***	**Difference**	***pre***	***post***	**Difference**
	Migra_pressure	1.0581	1.1898	0.1316	1.9372	2.0480	0.1108
	Comparable	1.2136	1.4252	0.2116	1.8396	2.1170	0.2773
	Difference T-C	-0.1555	-0.2355	-0.0800	0.0975	-0.0690	-0.1665
		Formal			**Informal**		
Q25	**Group**	***pre***	***post***	**Difference**	***pre***	***post***	**Difference**
	Migra_pressure	1.3014	1.6599	0.3585	1.2360	1.2772	0.0413
	Comparable	1.2801	1.7466	0.4665	1.1945	1.3059	0.1115
	Difference T-C	0.0213	-0.0867	-0.1080	0.0415	-0.0287	-0.0702
		Formal			**Informal**		
Q50	**Group**	***pre***	***post***	**Difference**	***pre***	***post***	**Difference**
	Migra_pressure	1.3119	1.4111	0.0992	1.2897	1.3217	0.0320
	Comparable	1.3075	1.4743	0.1667	1.2645	1.3945	0.1300
	Difference T-C	0.0044	-0.0632	-0.0675	0.0253	-0.0728	-0.0980
		Formal			**Informal**		
Q75	**Group**	***pre***	***post***	**Difference**	***pre***	***post***	**Difference**
	Migra_pressure	1.3233	1.3882	0.0649	1.3320	1.4128	0.0808
	Comparable	1.3328	1.4533	0.1205	1.3136	1.5125	0.1989
	Difference T-C	-0.0095	-0.0651	-0.0556	0.0184	-0.0997	-0.1181
		Formal			**Informal**		
Q90	**Group**	***pre***	***post***	**Difference**	***pre***	***post***	**Difference**
	Migra_pressure	1.2985	1.3874	0.0888	1.3196	1.2935	-0.0262
	Comparable	1.3408	1.4895	0.1487	1.3118	1.4288	0.1170
	Difference T-C	-0.0423	-0.1021	-0.0599	0.0078	-0.1353	-0.1432

Source: created by the authors based on the results of the models

When comparing the group of regions with low migration, nonetheless, they show a greater improvement than those with high migration, which means that, in general terms, it is possible that incomes have not fallen due to migration but rather that the incomes of the group with low migration have increased more. This impact is greater in informal employment, as would be expected because most migrants are in a hurry to find income and have easier access to informal than to formal employment. This indicates that, although there is a decrease in wages—mostly in informal jobs in the lower part of the distribution—it cannot be concluded that wages decreased but rather that they grew at a slower rate than those of the low migrant group.

The aforesaid can be explained by the evolution of other factors such as human capital, labor demand and its dynamics and the impact of higher unemployment rates between 2015 and 2019 that led to greater competition in larger regions (which are the ones that received greater migration), among other factors.

The above is confirmed in Table 6, which shows the interquantile ranges and shows mainly whether the variables in the model explain the differences between the different quartiles. The results show that the differences between quartiles that would explain the mobility of wages lie in variables such as education, which explains the interquartile difference at all levels except in the 25th and 10th quartile group, which reflects the fact that more schooling allows for an increase in wage income in the middle and upper part of the distribution in the formal segment of the labor market. Nonetheless, they have the same effect in the informal segment in the difference between the high and low and high and medium parts—with lower coefficients than the formal—but with a negative sign in the difference between groups of 75-50, 50-25, and 25-10, so that people with high education at these levels of income distribution are affected by their very level of education. This is explained by the fact that people with more schooling more easily enter the formal segment, and those who must enter the informal segment explain the wage differences by other factors or variables related to job search channels, work experience or role in the household.

Other variables, such as being head of household and being married, explain these differences. The sex variable shows that being male explains this difference in the distribution in the formal segment but not in the informal segment. In that case, being male implies having less mobility toward higher wages, and in the case of informal employment, being female is what explains this difference. This again reflects a considerable gender difference that is not only in employment but also in wages, which affects women in the entire labor market. The same occurs with young people, who in both labor segments have negative coefficients; therefore, being young leads to lower salaries and little upward mobility, mainly explained by their lack of work experience.

In the case of the core variable of the study, it is observed that the effect of the treatment group over time, that is, regions with high migration, does not explain the interquantile differences; it is only statistically significant in the difference between quartiles 25 and 10, which is consistent with the results in Table 6. Consequently, migration affects lower incomes and the informal sector, so competition is higher in this labor market segment.

Table 6. Interquantile differences

Variables	Q90-Q10				Q90-Q75				Q90-Q50			
	Formal	P-Value	Informal	P-Value	Formal	P-Value	Informal	P-Value	Formal	P-Value	Informal	P-Value
Migra_ pressure	0.0245	0.0000	0.0534	0.0000	0.0079	0.1050	-0.0017	0.6650	0.0268	0.0000	0.0066	0.1320
Time	-0.0576	0.0000	0.0262	0.0020	-0.0267	0.0000	-0.0368	0.0000	-0.0451	0.0000	-0.0231	0.0000
Time_migra	0.0142	0.1720	-0.0199	0.1960	0.0132	0.0320	0.0195	0.0000	0.0052	0.4760	0.0163	0.0550
Sex	-0.1117	0.0000	-0.8045	0.0000	0.0370	0.0000	-0.0456	0.0000	0.0994	0.0000	-0.3084	0.0000
Head of household	0.0450	0.0000	-0.1637	0.0000	0.0199	0.0000	0.0360	0.0000	0.0586	0.0000	-0.0017	0.7240
Marital status	0.0346	0.0000	0.0240	0.0000	0.0187	0.0000	0.0248	0.0000	0.0376	0.0000	0.0480	0.0000
Secondary School	-0.0365	0.0000	-0.0601	0.0000	0.0841	0.0000	0.0519	0.0000	0.1514	0.0000	0.0409	0.0000
Technical level	0.0636	0.0000	0.0318	0.0610	0.0924	0.0000	0.0780	0.0000	0.2559	0.0000	0.0747	0.0000
University level	0.6669	0.0000	0.0574	0.0880	0.1390	0.0000	0.2435	0.0000	0.3682	0.0000	0.2904	0.0000
Postgraduate level	0.4617	0.0000	0.2886	0.0000	0.1696	0.0000	0.1573	0.0020	0.3045	0.0000	0.2909	0.0000
Young people	-0.0781	0.0000	0.0288	0.1330	-0.0261	0.0000	-0.0018	0.7650	-0.0635	0.0000	-0.0109	0.2000
_cons	1.0914	0.0000	2.573.364	0.0000	0.1724	0.0000	0.2621	0.0000	0.2732	0.0000	0.8863	0.0000

Variables	Q75-Q25				Q50-Q25				Q25-Q10			
	Formal	P-Value	Informal	P-Value	Formal	P-Value	Informal	P-Value	Formal	P-Value	Informal	P-Value
Migra_ pressure	0.0217	0.0000	0.0151	0.0640	0.0028	0.2920	0.0068	0.0940	-0.0050	0.2190	0.0400	0.0000
Time	-0.0285	0.0000	0.0176	0.0230	-0.0101	0.0000	0.0039	0.4040	-0.0024	0.6140	0.0454	0.0000
Time_migra	-0.0033	0.5210	0.0031	0.7660	0.0047	0.2210	0.0063	0.3950	0.0043	0.4960	-0.0425	0.0000
Sex	0.0470	0.0000	-0.5509	0.0000	-0.0154	0.0000	-0.2882	0.0000	-0.1957	0.0000	-0.2079	0.0000
Head of household	0.0537	0.0000	-0.1307	0.0000	0.0150	0.0000	-0.0929	0.0000	-0.0286	0.0000	-0.0691	0.0000
Marital status	0.0264	0.0000	0.0239	0.0000	0.0075	0.0000	0.0007	0.8660	-0.0104	0.0230	-0.0247	0.0030
Secondary School	0.0501	0.0000	-0.0835	0.0000	-0.0171	0.0000	-0.0724	0.0000	-0.1708	0.0000	-0.0285	0.0000
Technical level	0.1922	0.0000	-0.0548	0.0000	0.0286	0.0000	-0.0515	0.0000	-0.2209	0.0000	0.0086	0.3270
University level	0.5286	0.0000	-0.0743	0.0000	0.2993	0.0000	-0.1212	0.0000	-0.0006	0.9320	-0.1118	0.0000
Postgraduate level	0.3153	0.0000	0.1337	0.0020	0.1803	0.0000	0.0001	0.9990	-0.0232	0.0030	-0.0023	0.9550
Young people	-0.0542	0.0000	0.0218	0.0570	-0.0168	0.0000	0.0308	0.0000	0.0021	0.7920	0.0088	0.5480
_cons	0.2722	0.0000	1.4924	0.0000	0.1714	0.0000	0.8681	0.0000	0.6468	0.0000	0.8189	0.0000

Source: created by the authors based on the results of the models

Discussion of the results

This paper reveals that migration is associated with an increase in precarious employment, especially in the informal sector. This could negatively affect the labor rights, social protection, and welfare of migrant workers. In addition, it is important to consider measures to strengthen the protection of migrants' labor rights and promote their access to formal and decent jobs.

The analysis also confirms the existence of gender gaps in the labor market, which are intensified in the context of migration. Migrant women face difficulties in accessing formal jobs, receive lower wages and are at greater risk of falling into precariousness. It is necessary to implement public policies that promote gender equity in the labor market and provide specific support to migrant women.

In addition, the study shows that young people are one of the groups most affected by migration in terms of access to decent jobs and wages. The lack of work experience and the difficulties of participation in the labor market are intensified in the context of migration. It is necessary to implement public policies that promote the inclusion of young migrants in the labor market and provide them with opportunities to develop their skills and competencies.

On the other hand, the analysis confirms the importance of education for better job opportunities, especially in the context of migration. People with higher levels of education are more likely to have access to formal jobs and receive better wages. It is necessary to strengthen education systems and promote access to quality education for all, including migrants.

The study also suggests that migration could be intensifying competition in the informal labor market, which could negatively affect the wages and working conditions of workers in this sector. There is a need to strengthen public policies to promote the formalization of employment and reduce informal employment, especially in the context of migration.

In general terms, it was observed that the employability of Venezuelan migrants also depends on socioeconomic factors such as educational level, age, sex and position as head of household. Thus, this population shows results similar to national results regarding women and young people being the most vulnerable, just as education benefits participation in the formal segment, and being head of household implies greater labor participation and employability in any segment. Nevertheless, a negative effect of mass migration was found in the regions with the greatest migration pressure. The occupational effect was mainly in the informal segment since it has increased the probability of being in precarious occupations, and in the labor supply, that is, there is a greater probability of being unemployed. Although there was also a negative effect in the formal segment, this may be determined by human capital factors and the dynamics of the economy.

Concerning wages, the results showed that wage impacts are greater in the informal segment and in the lowest quantiles of the distribution, which is related to the fact that most of the migrants' employment is in the informal segment. Accordingly, wages were negatively affected by increasing the pressure on employability in the informal sector, which is worrisome because it increases the vulnerable population (with low incomes). Notwithstanding, this effect may be because, in regions with low migration pressure, average income increased more than the increase in regions with high migration pressure.

Similarly, the impact on wages is largely explained by factors such as education, sex and being head of household. Again, in addition to migration, the impact on employment and wages depends on the same factors and differences as the national population, that is, the labor market can discriminate, in market terms, against employability due to socioeconomic characteristics that are not clearly related to migration, with the exception that migrants—for legal reasons of educational degrees or other reasons—can easily enter informal employment while overcoming these barriers. Nevertheless, the fact of being a migrant can be subject to discrimination in the market, meaning that migrants do not have as many possibilities of participating in the formal segment due to lack of legal documents or haste in obtaining income, that is, they cannot remain in the job search for a long period.

This effect on formal employment status is analyzed by Bahar et al. (2021), who observed a positive and significant effect of the program granting work permits to forced migrants on the formal employment of Venezuelan migrants, implying that the Special Permit to Stay (PEP, Spanish acronym of Permiso Especial de Permanencia) program is indeed succeeding in getting Venezuelan workers to join the formal labor market.

On the other hand, the results of this study are consistent with those obtained by other authors. On the one hand, Bonilla-Mejía et al. (2020) state that the loss of employment has been concentrated in small companies, while no significant effects were detected for large companies, which consequently meant that immigration also had negative and significant effects on wages since it allowed for cheaper labor costs. On the other hand, Tribín-Uribe et al. (2020) found that the most affected sector is the informal sector and that migration from Venezuela has no effect on the variables of the formal sector.

Conclusions

The impact of the mass migration of Venezuelan citizens between 2016 and 2018 implies a challenge in labor terms for a highly informal economy and a segmented labor market such as the Colombian one. The literature has shown that migration can bring economic growth and human capital utilization benefits. Nonetheless, this will depend on how this population is integrated into the labor market.

On the other hand, the review of the literature also reflects a problem of vulnerability of migration in labor terms since being a migrant leads to hiring complications, especially for migrants who do not have easy access to legalization (bureaucratic procedures) that would allow them to compete in the formal sector. This is especially problematic for people with high educational levels since they aspire to enter the formal segment and cannot do so, which reduces their salary prospects and complicates their job search. It is also a social and economic cost for the countries receiving migrants since they cannot take advantage of the productivity of the migrants' more educated labor force, which is a waste from the point of view of productivity and social protection.

Likewise, recent studies on the impact of migration reflect that they enter informal employment and increase the vulnerable population of the countries they arrive in, which is consistent with this study's results and reinforces this idea of vulnerability and informal employment. Furthermore, when observing the behavior of wages, it is found that the negative impact is seen in lower wage growth in the regions with the greatest number of migrants, especially in the lower parts of the wage distribution and in the informal sector.

In this regard, this research makes a notable contribution to the differentiation of the impact by labor segmentation, where it is specifically distinguished that the greatest effect of migration is in the informal segment and where it is observed that socioeconomic characteristics define the probability of employment and better wages in both the informal and formal segments. Moreover, the vulnerability of migrants may have additional conditions of low probability of employment and low wages because of being female, being young, not being heads of household or having a low level of education. This is similar to native workers, so the labor market discriminates in these terms against the entire labor force but makes a greater distinction of labor segmentation in migrants. This opens the door to analyzing in subsequent research whether the limits to the formalization of migrant labor due to lack of work permit documents lead to increased vulnerability of this population or the effects of labor demand and human capital gaps that may limit this connection between migrant labor supply and formal job vacancies.

Hence, the public policy to mitigate the migration problem should focus on preventing migrants, especially the most educated, from becoming part of the informal sector. Likewise, the range of social protection should be broadened—even more so in times of crisis such as the pandemic—where the fall in wages is deeper at the bottom of the wage distribution and even deeper in the informal sector. These measures will not only help protect migrants but will also contribute to greater economic and social stability in the receiving country by increasing consumption capacity and fiscal revenues.

Finally, it was possible to demonstrate that mass migration did not have the harmful effects that can be intuited in different areas. Migrants have increased their probability of employability, but in the informal segment, and it has not been at the cost of a worsening of the employment of native workers. The only notable impact was on the wages of already vulnerable people in possible informal employment traps who face a significant increase in the supply of informal labor from migrants. This leads to the need for public policy intervention for the entire vulnerable lower-income population in informal employment.

Thus, this study provides a valuable analysis of the impact of migration on the labor market, highlighting the importance of considering labor segmentation, the socioeconomic characteristics of migrants, and the interactions between different types of vulnerability. Additional efforts are needed to better understand the complex dynamics between migration, labor market and social development. Public policies should be designed comprehensively, considering the specific needs and challenges of different groups of migrants, to promote social integration, equity and well-being for all members of society.

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Cristian Dario Castillo Robayo
Colombian. PhD in Economics from the Universidad Autónoma de Madrid. Professor-researcher at the Faculty of Economics of the Universidad de los Llanos. Research lines: labor market, vulnerable population, economic development, experimental economy and poverty. Recent publication: Da Silva Bichara, J., Castillo Robayo, C. & Delgado, J. L. (2022). La informalidad y la duración del desempleo de los jóvenes en Latinoamérica. Especial referencia a Ecuador. *Revista de Economía Mundial*, (60), 125-149. https://doi.org/10.33776/rem.vi60.5470

William Prieto
Colombian. Master's degree in public policy from Rochester University. Researcher at the Faculty of Economic and Administrative Sciences, Universidad Católica de Colombia. Research lines: applied economics, labor economics and institutional economics. Special interest in estimating the effects of institutional regulations on the labor market and effects of asymmetric information on labor contracts. Recent publication: Prieto Bustos, W., Castillo Robayo, C. D., Campo Robledo, J. & Molina Dominguez, J. (2024). Impact of Venezuelan migration on the informal workforce of native workers in Colombia. *Economies*, *12*(2), Article 38. https://doi.org/10.3390/economies12020038

Jacobo Alberto Campo Robledo
Colombian. Master's degree in economics from the Universidad del Rosario (Colombia). Researcher at the Faculty of Economic and Administrative Sciences of the Universidad Católica de Colombia. Research lines: economic growth, applied econometrics and labor market. Recent publication: Villar Otalora, J. C. & Campo Robledo, J. A. (2024). Análisis empírico de la relación entre investigación, desarrollo, innovación y crecimiento económico en países OCDE. *Revista de Métodos Cuantitativos para la Economía y la Empresa*, 1-13. https://doi.org/10.46661/rev.metodoscuant.econ.empresa.7900