The distributional effect of a migratory exodus in a developing country: the role of downgrading and regularization*

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Abstract

We study the distributional effect of the massive exodus of Venezuelans in Colombia and how public policy can shape its impact. Using RIF-regressions in an instrumental variables approach, we find that the exodus had a larger negative effect on the lower tail of the natives' wage distribution, increasing inequality in the host economy. We propose downgrading as the driving mechanism: due to formal restrictions, immigrants ended up working in more routine and lower-paying jobs than natives with similar characteristics. Finally, we show that a large-scale amnesty program reduced the magnitude of downgrading, mitigating the unequalizing impact of the exodus.

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1 Introduction

Expelled by severe economic crises, food shortages, insecurity and human rights violations, millions of people are forced to leave their homes each year. In 2020, above one percent of the world's population was forcibly displaced –a dramatic 67% increase in the last decade[1]– (UNHCR, 2020). Among other consequences, episodes of massive migration can potentially disrupt labor markets and affect economic inequality in hosting economies (Borjas, 2017; Borjas and Monras, 2017; Dustmann et al., 2013). Although dealing with this phenomenon is a central concern of governments around the world, not enough is known about the channels by which migration affects the income distribution or the policies oriented at tackling the disruption brought by the newly arrived. This paper contributes to filling these gaps by studying the distributional effects of a large immigration inflow and how a public policy aimed at integrating and legalizing immigrants shapes its economic impact.

The Venezuelan exodus is the second most important episode of forced migration in the world: 4.9 million people left their home country due to the social and economic crisis; a staggering 16% of Venezuela's population (UNHCR, 2020). Most of them sought to start a new life in neighboring Colombia: between 2016 and 2019, almost 1.7 million Venezuelans crossed the border to this country (UNHCR, 2020). The nature of the Venezuelan exodus determined that the settlement of refugees in Colombia took place under very vulnerable conditions: despite being at least as skilled as their Colombian counterparts, Venezuelan workers earn an average hourly wage 28% lower relative to Colombians, have an unemployment rate 40% higher, and are 60% more likely to be below the poverty line.

In 2018, to assess their living conditions, the Colombian government implemented a broad census of forced migrants followed by an unexpected amnesty program that allowed Venezuelan immigrants to work in the formal labor market and access public services such as health and education. About 16% of the estimated total number of Venezuelans living in Colombia at that time were granted with residence permits.

In this paper we tell the story of the distributional impact of the mass migration of Venezuelans in Colombia in three parts. (i) In the first one, we assess the initial impact of the exodus on the income distribution of natives, and find a puzzling result: although migrants are at least as skilled as native workers, migration reduced wages especially in the lower tail of the earnings distribution and then became a significant unequalizing factor on the income distribution. (ii) In the second part, we unveil a likely factor behind this result: the downgrading of skilled migrants who end up working in high-routine low-paid jobs, due to the lack of legal permits to do so in the formal high-skilled segment of the labor market. (iii) Finally, in the third part we study how a large amnesty program that allowed Venezuelan immigrants to work in the formal labor market helped alleviating the downgrading factor, and hence mitigating the unequalizing

[1] According to UNHCR (2020), whereas in 2010, 1 in 159 people worldwide was forcibly displaced, by 2020 that ratio is 1 in 95.

initial impact of the exodus. In each part of this story about the distributional impact of massive forced migration, we apply a different methodology and make some contributions to the literature.

First, to assess the initial impact of the Venezuelan immigration in Colombia we implement a novel combination of Recentered Influence Function (RIF) regressions in a Bartik-type instrumental variables (IV) approach.[2] On the one hand, RIF-regressions allow us to estimate the distributional effects of immigration on natives' income. On the other hand, the IV approach helps to account for the non-random location of immigrants in Colombia when exploiting geographical heterogeneity. Our results show that the Venezuelan exodus caused unequalizing distributional changes: looking at a broad set of inequality measures, we find that immigration increased income inequality. This effect is driven by a large negative impact in the left tail of the earnings distribution, likely explained by greater competition between migrants and natives in low-income jobs.

Our estimated distributional effects of immigration seem to be at odds with the fact that Venezuelan immigrants are, on average, at least as skilled as native Colombian workers; a distinctive novel feature of Venezuelan immigration with respect to other migration shock episodes such as those in developed countries. We propose a mechanism to explain these apparently puzzling results: the downgrading of Venezuelan migrants in terms of the tasks they perform and wages they earn. We construct counterfactual density functions to assess whether there is downgrading in wages and routinization of tasks performed by immigrants with similar sociodemographic characteristics to those of natives. Our results show that Venezuelan immigrants work in more routine tasks occupations and earn lower wages than natives with similar educational and sociodemographic characteristics. They also participate mainly at the informal sector.

These results may be explained by the fact that immigrants were unable to work formally. Specifically, Venezuelan skilled migrants without work permits could not legally sell their labor force in the high-skilled segment of the Colombian labor market. In a similar framework to that of Monras et al. (2021), at an upper level the labor market in Colombia can be thought as segmented in two labor types that are imperfect substitutes in production: a high-skilled segment and a low-skilled one. In the first one, there are no informal workers (or it is very difficult for firms to hire informal labor). In our set-up, as a novelty, this forces immigrants to downgrade and sell their labor force informally in the low-skilled segment, where there are two types of employment: formal and informal (both of these labor market inputs are also imperfectly substitutable to employers). This uneven distribution of the labor supply shock due to the constrained choice set of Venezuelan workers in the Colombian labor market explain the excess pressure on the low-income segment of the Colombian income distribution and, hence,

[2] RIF-regressions have recently become more popular for analyzing distributional impacts of different events. See, for instance, Dube (2019).

the found unequalizing effect of the Venezuelan exodus. Indeed, we show evidence that in the lower part of the income distribution of natives these two phenomena occur simultaneously: there are more migrants working than there should be if they were remunerated like natives (according to their characteristics) and the negative effect of immigration on income is larger.

Finally, in the last part of the paper, we show that public policies, such as mass amnesty programs for undocumented refugees, can mitigate the downgrading of immigrants, and the consequent unequalizing impact of forced migration. To do so, we analyze the implementation of a massive regularization program carried out by the Colombian government in 2018 that unexpectedly regularized more than 280.000 Venezuelan undocumented immigrants: the *Permiso Especial de Permanencia - Registro Administrativo de Migrantes Venezolanos* (PEP-RAMV).

We exploit the geographic variation in the number of regularized migrants and instrument it, following Bahar et al. (2021), with a measure of the exogenously allocated number of days available in each department of Colombia to register for the amnesty program. Thus, we follow an instrumental variables difference-in-difference strategy to analyze the effect of the PEP-RAMV combining the instrument just mentioned with the Bartik-type instrument used in the first part of this paper. When focusing on the sample of Venezuelan immigrants, we find that the program had mitigating effects on downgrading in terms of wages and increased the probability of having a skill-intensive job, which represents an improvement in the employees-jobs matching in terms of skills. We further find evidence of the program lowering the desire of highly educated Venezuelan workers to change jobs due to their self-perceived underutilization of skills or training. In other words, the program enlarged the labor supply choice set of forced migrants who, prior to amnesty, were forced to downgrade and sell their labor force in the low-skilled informal segment and who, after the policy, can find a better match with their skills in the formal labor market. Then, we go back to our estimated distributional effects of immigration and find that the amnesty program had an equalizing impact. This partially offsets the initial negative effect that the migration had on the income distribution by possibly alleviating the pressure among native workers with lower labor incomes. Finally, we analyze alternative explanations to our results and show different robustness and internal validity checks.

This paper relates to three major strands of the economic literature. The labor market impact of migration episodes and refugee waves has been thoroughly studied by economists both in developed (see, for instance, Card, 1990; Hunt, 1992; Borjas, 2003; Foged and Peri, 2016) and developing countries. In particular, there is a growing number of analyses related to developing-developing migration, especially motivated by episodes of forced migration such as the ones in Syria (Altındağ et al., 2020; Tumen, 2016; Cengiz and Tekgüç, 2022; Malaeb et al., 2018) and Venezuela (Caruso et al., 2019; Peñaloza-Pacheco, 2019; Lombardo and Peñaloza-Pacheco, 2021; Delgado-Prieto et al., 2021; Santamaria, 2020; Olivieri et al., 2021; Morales and Pierola, 2020). For developed countries Borjas (2017) and Borjas and Monras (2017) study the distributional consequences of refugee inflows and rationalize their results through the laws of supply and demand. Also Card (2009), and Dustmann et al. (2013) stand out in terms of their analyses of the effect of migration on inequality and the downgrading of immigrants in the U.S. and the U.K., respectively. For developing countries, however, evidence on the impact of migration on inequality is scarce.[3] Our paper contributes to this still infant literature in the developing world by assessing the distributional impact of one of the largest forced migration episodes with a novel framework, RIF-regressions, which allows us to analyze the effect of immigration at different points of the income distribution and on specific inequality measures. This more granular analysis allows us to better characterize the effect of migration on the income distribution than previous analysis. Moreover, the context is also different to most other papers, since we focus on a developing country receiving a massive flow of migrants who are not less skilled than natives.

Other group of papers in the literature study how massive migratory integration and amnesty programs affect several natives' and immigrants' outcomes in the hosting economies (see Kossoudji and Cobb-Clark, 2002; Bratsberg et al., 2002; Devillanova et al., 2018; Monras et al., 2021; Bahar et al., 2021, for examples). In a closely related paper, Bahar et al. (2021) analyze the heterogeneous effects of the PEP-RAMV amnesty program on labor market outcomes. Overall, the authors find no economically significant effect of the amnesty program. In our paper, however, we analyze the program through the lenses of the distributional effects of immigration, and show how the public policy partly offset the initial unequalizing effect by positively affecting immigrants labor market integration.

Finally, this paper relates to a growing literature that analyzes the role of labor market frictions in the economic impact of immigration (Monras et al., 2021; Piracha et al., 2012; Chiswick and Miller, 2009; Eckstein and Weiss, 2004; Friedberg, 2000; Lebow, 2021; Naidu et al., 2016; Amior and Manning, 2022). We contribute to this literature by showing how a large-scale amnesty program that reduced some of these labor market rigidities affected the downgrading of immigrants in terms of wages and routinization of performed tasks, and, more in general, their job opportunities.

The rest of the paper is organized as follows. Section 2 shows information on the Venezuelan social and economic crisis and the subsequent migratory exodus. Section 3 presents the data source used in the paper and some descriptive statistics. Section 4 analyzes the effect of the Venezuelan migratory exodus on different indicators of income distribution by: (i) introducing the empirical strategy used, and (ii) showing the main results on the income distribution. Section 5: (i) presents the empirical strategy carried out to asses the main drivers of the

[3] Gindling (2009) finds no statistical relationship between the Nicaraguan migration and poverty and inequality in Costa Rica, but his empirical approach does not allow for a causal interpretation of the effect of migration on inequality. Akgündüz et al. (2015), on the other hand, study the labor market impact of the Syrian refugees on low- and high-educated Turkish workers. Nevertheless, they do not directly address the inequality generated by the wave of Syrian forced migrants.

inequality results found, and (ii) puts forth the analysis of these channels. Section 6: (i) describes the amnesty program implemented by the Colombian government; (ii) provides an extension of the empirical strategy described in Section 4 to carry out the analysis of this program, and (iii) studies its consequences in terms of inequality and labor integration of immigrant workers. Section 7 discusses the internal validity and some potential concerns about the empirical strategy as well as alternative mechanisms. Finally, Section 8 concludes.

2 Context

2.1 The Venezuelan exodus

The *Chavismo*, headed by its leader Hugo Chávez, took office in Venezuela in 1999 and has governed since. During Chavez's government, which ended in 2013 with his death, populist economic policy measures were implemented with high public spending that increased domestic consumption. These policies were based on resources coming from the high prices of commodities, mainly oil on which most of the country's fiscal and external revenues relied.[4] However, since 2013, when Nicolás Maduro assumed the presidency of Venezuela as Chávez's successor, the international reference price of oil fell from close to USD 120 per barrel in early 2012 to a minimum of close to USD 25 in early 2016 (Rozo and Vargas, 2021).

This reduction in government revenues along with unsustainable levels of public debt and macroeconomic imbalances led to an unprecedented economic crisis that generated, according to estimates by CEPAL (2019), a 62.2% drop in GDP in the 2013-2019 period. This economic crisis, combined with food shortages, insecurity and multiple human rights violations by the government resulted in an environment where chaos, uncertainty and social crisis reigned (UN Human Rights, 2019). This situation triggered a massive exodus of Venezuelans (approximately 4.9 million Venezuelans) who have had to leave their country to seek a new future in other countries, mainly in Latin America. Given the geographical proximity, Colombia has been the main destination of Venezuelan migrants: more than 1.7 million immigrants have arrived in the last five years (Castillo Crasto and Reguant Álvarez, 2017; UN Human Rights, 2019; UNHCR, 2020).

The reopening of the borders between Colombia and Venezuela in August 2016, after nearly a year of being closed due to political tensions between the governments of both countries, boosted the massive exodus. Panel (a) of Figure 1, shows the monthly stock of Venezuelan immigrants living in Colombia over the 2013-2019 period. After the borders re-opening (vertical dashed line) the number of Venezuelans settled in Colombia increased significantly reaching its maximum in 2019.

Furthermore, panel (b) of Figure 1 shows the share of Venezuelans relative to the local

[4] In the early 2010s oil represented more than 90% of Venezuela´s exports and the public fiscal deficit represented more than 17% of the domestic GDP.

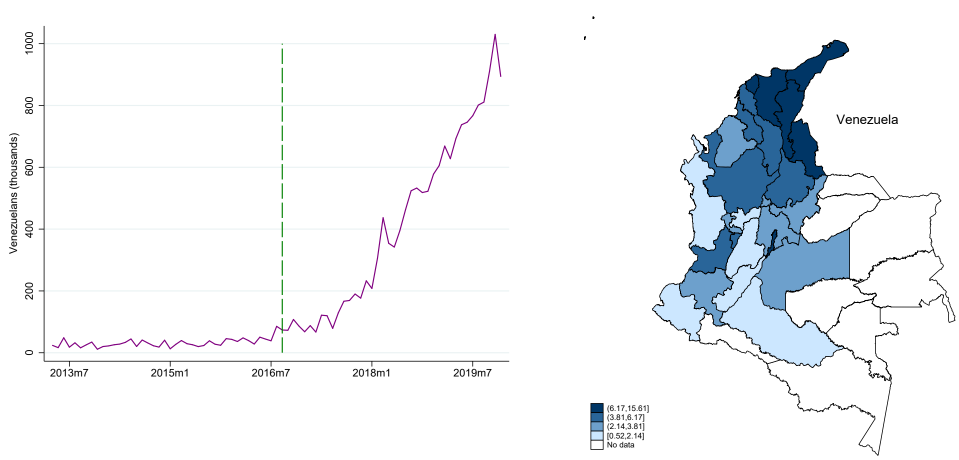
population for each department of Colombia in 2019. The share ranges between 0.5% in some departments in the south and west of the country to more than 15% in those departments located close to the border with Venezuela such as La Guajira and Norte de Santander. This pattern according to which the closer the department is located to the Colombian-Venezuelan border the higher the share of Venezuelan immigrants is explained by the flight character of the Venezuelan exodus (an episode of forced migration) and is crucial for our identification strategy (see Section 4.1).

Due to this forced nature of the migration, Venezuelan immigrants initially faced several constraints to regularize their migratory situation in Colombia and to legally integrate to the society. Immigrants did not have access to public services like health and education services. They were unable to participate actively in the formal labor market and to validate their educational credentials attained in their country of origin (Bahar et al., 2021). To mitigate this situation, the Colombian government implemented a special residency permit called *Permiso Especial de Permanencia (PEP)* to formalize and regularize Venezuelan immigrants in Colombia (See Section 6 for more details). Yet, according to official statistics from the Migration Unit in Colombia, more than half of the Venezuelans in Colombia were in an irregular situation by the end of 2019.

Figure 1: Venezuelan exodus in Colombia

(a) Number of Venezuelans over time

(b) Share of Venezuelans by department (2019)



Notes. Panel (a) shows the stock of Venezuelan-born people in Colombia over time. Dashed vertical line indicates the moment in which the borders between Colombia and Venezuela were re-opened. Panel (b) exhibits the share of Venezuelan-born people relative to the local departmental population. Departments with no data are mainly departments in the Amazon region with a low population density and small main cities in which data is not available. According to the last available census in Colombia (2018), population in these departments represents less than 3% of the total population in Colombia.
Source. Own elaboration based on data from DANE.

3 Data and Descriptive Statistics

3.1 Data

To conduct our analysis we use the Gran Encuesta Integrada de Hogares (GEIH, by its acronym in Spanish) of the Departamento Administrativo Nacional de Estadística (DANE), a nationally representative household survey carried out at a monthly basis in urban and rural areas of Colombia. The GEIH is a repeated cross-sectional survey that includes socio-demographic and economic information on employed, unemployed and inactive individuals. Since April 2013, the GEIH also includes detailed information on respondents' place of birth and area of residence for the previous 5 years and 12 months. We consider the period 2013-2019 and restrict the sample to native individuals (i.e., we exclude from our sample individuals who reported being born in another country). The working database is composed of 4,860,555 observations from 24 departments of Colombia out of a total of 32.[5]

For analyzing the degree of routinization of tasks in each worker's occupation we rely on the Routine Task Content (RTC) indices constructed by Gasparini et al. (2021) from the Programme for the International Assessment of Adult Competencies (PIAAC) surveys conducted by the OECD.[6] The authors construct the routine index from the following four questions: (i) Do you manage or supervise other people?; (ii) Do you plan activities of other workers?; (iii) Are you confronted with problems?; and (iv) Do you write articles or reports? According to them, these four questions provide information about thinking, flexibility and problem-solving skills that are not threatened by the implementation of new technologies (i.e., they are less routine and less prone to being automated). The routine index we consider in our analysis is the RTC-PIAAC index of Gasparini et al. (2021) which indicates the percentage of individuals for each occupational level (according to the ISCO-08 classification) who do not perform any of the non-routine tasks mentioned above. Therefore, the higher the RTC-PIAAC index, the more routine that occupation is. Then, we match each routine index at the occupational level with the GEIH information in Colombia considering the ISCO-08 classification.[7] In other words, the RTC index indicates the average routine task content of each occupation.

Data on the amnesty program comes from Bahar et al. (2021). Although microdata is confidential, we use aggregate numbers of Venezuelans regularized in each Colombian department through the whole implementation of the program. For descriptive statistics, we rely on the

[5] The departments for which data are not available are: Amazonas, Vaupés, Guainía, Guaviare, Vichada, Arauca, Casanare and San Andrés. In these departments the GEIH is not carried out with the same periodicity as in the rest of the country. For this reason, these departments will not be considered in the analysis. However, according to the latest Census in Colombia (2018), the population of these eight departments represents about 3% of the population in Colombia because they are mainly rural regions. Therefore, the results presented here should not be affected.

[6] They use data from the four Latin American countries included in the survey: Chile, Ecuador, Mexico and Peru.

[7] We do not use the Colombian occupational classification of SENA (Clasificador Nacional de Ocupaciones 1970), but the equivalences to ISCO-08 provided by the World Bank and CEDLAS.

authors' work.

3.2 Socio-demographic characteristics of Colombians and Venezuelans

Table A.1 of Appendix A presents several descriptive statistics for Colombians and Venezuelans in our sample. We show overall statistics for Venezuelans and Colombians in the first two columns. In the last two columns of the table we split Venezuelan immigrants between those who arrived to Colombia 5 years ago and 1 year ago in 2019, respectively. We group descriptive statistics in two: Panel A shows socio-economic characteristics (age, sex, living conditions, etc.) for all individuals, and Panel B presents labor characteristics for those individuals who were working when surveyed.

We find that Venezuelan immigrants are, on average, younger, have a lower socio-economic level and are more likely to live in urban areas. This does not depend on when they arrived in Colombia. Moreover, Venezuelans are more likely to participate in the labor force compared to natives but have a higher probability of being unemployed. All these characteristics are consistent with the expected self-selection of those forced migrants who left Venezuela in search of new opportunities in a different country and are also expected given the difficult conditions that forced migrants face in terms of labor opportunities when they arrive in a new country. These characteristics translate into higher poverty and extreme poverty rates for Venezuelan immigrants (56.3% and 15.5%, respectively) than those of Colombians (35.7% and 9.8%, respectively); when considering only Venezuelans who arrived 1 year ago, both rates are almost double (61.2% and 17%) compared to the local population.

A very important feature of this episode of forced migration compared to those episodes usually studied in the economic literature refers to the educational composition of Venezuelan immigrants relative to that of natives. Panel A of Table A.1 also shows that Venezuelan immigrants have, on average, at least the same years of education as Colombians. When classifying individuals by educational level, we find that the main difference arise in completed secondary school: there is a significantly higher proportion of Venezuelan immigrants with completed secondary school (25.5%) compared to that of Colombians (20.5%).[8]

In Panel B of Table A.1 we analyze the characteristics of the native and Venezuelan working population. First, Venezuelans earn an average hourly wage about 27% lower compared to Colombian workers; this difference seems to be close to 38% when we consider only Venezuelan immigrants with one year of residence in Colombia. This significant difference in terms of hourly earnings for Venezuelan immigrants may be part of the explanation for the higher poverty rates among immigrants compared to natives. In addition, we find that Venezuelans in the labor market work, on average, at least 4 to 5 hours per week more than Colombian

[8] Since quality of secondary and post-secondary education is similar between Colombia and Venezuela, it is reasonable to consider that Venezuelan and Colombian skilled workers have similar abilities. See Lebow (2021) for further discussion and detailed analysis.

workers and that they have jobs with more routine tasks compared to native workers. All in all, although Venezuelan immigrants have a similar (or even higher) level of education compared to Colombians, they experience much higher unemployment rates, have lower income levels and, consequently, live in much tougher conditions in terms of poverty.

In the last part of Panel B in Table A.1 we show the distribution of Colombian and Venezuelan workers by economic sector. We observe that Venezuelan immigrants are significantly more concentrated in commercial activities (46.2%), construction (11.7%), low-tech industries (7.4%) and domestic service (3.9%) compared to Colombian workers. Also, although the education levels of Venezuelans are similar to those of Colombians, they are less represented in high-skilled economic sectors such as high-tech industries (4%) and skilled services (4.7%). In turn, the participation of Venezuelan workers in the public administration is practically zero. This distribution of the Venezuelan labor force across economic sectors is consistent with the fact that immigrants are less likely to participate in economic sectors with higher rates of formality due to the barriers they face in terms of regularization. These legal constraints push them to economic sectors with more flexible admission and participation processes such as commerce and construction, where informality rates are higher.

3.3 Income distribution in Colombia

Colombia is one of the most unequal countries in Latin America (Tornarolli et al., 2018). According to data from SEDLAC (CEDLAS and World Bank), the Gini coefficient in Colombia has been reduced in the last decade. However, it is still above the average value for the region.

In Table A.2 of Appendix A, we show several inequality and poverty indicators calculated based on GEIH data in Colombia. Our estimates indicate that income inequality seems to have an overall decreasing behavior during the 2013-2019 period regardless of the indicator considered, with a particular break point in 2018: there was a significant drop in income inequality during 2013-2017; however, from 2018 onward there seems to be an increase in inequality in the country that did not reverse the reduction of previous years. In terms of poverty, the trend is similar: in 2013, 38.7% of Colombians were below the poverty line and this proportion reached its minimum in 2018 when the poverty rate decreased by 2.4 percentage points. Yet, in the last year of our sample we observe an increase in all poverty indicators considered in our estimates.

This significant change in the trends in terms of inequality and poverty during the 2018-2019 period coincides with the period in which the Venezuelan exodus took place and intensified. Although with this preliminary information we cannot argue that the deterioration of these social indicators can be explained by Venezuelan immigration, it is suggestive evidence of the potential regressive effects of this episode of forced migration.

Figure A.1 of Appendix A shows the heterogeneity of income inequality and income level across departments in Colombia before the beginning of the Venezuelan migratory exodus

(2013). There seems to be significant variability in both variables across departments: there are departments where inequality is significantly below the national average such as Sucre, Caquetá and Atlántico; on the other hand, departments such as Chocó, La Guajira and Cauca have the highest income inequality. It is also worth mentioning that income inequality appears to be significantly high regardless of the level of per capita income: for example, Antioquia and Chocó are among the departments with the highest income inequality; however, they are also departments with the highest and lowest income levels, respectively.

4 The effect of the Venezuelan exodus on Colombian income distribution

4.1 Empirical strategy for estimating the effect of immigration

In order to estimate the effect of the Venezuelan exodus on several indicators of income distribution, we implement Recentered Influence Function (RIF) regressions. This allows us to obtain a first-order approximation to a large variation in the distribution of X (our explanatory variables) in the statistic $\nu(F_Y)$ or can be used to estimate the effect of a "small change" in the distribution of X in $\nu(F_Y)$, given individuals' characteristics (Firpo et al., 2009). In this first part of the paper we study the effect of a marginal increase in migration, given the characteristics of individuals, on several indicators of the unconditional (marginal) distribution of per capita income and labor income for the 2013-2019 period.

More formally, the average derivatives calculated using RIF-regressions produce the partial effect of a small location shift in the cumulative distribution function of the covariates X on the distributional statistic of interest. Firpo et al. (2009) call this parameter "unconditional partial effect" (UPE):

$$\alpha(\nu) = \int \frac{dE[RIF(y,\nu)|X=x]}{dx} dF_X(x) \tag{1}$$

By approximating conditional expectations with linear functions, RIF-regression coefficients indicate the extent to which the functional (in our case the quantile, Gini, Atkinson, and Entropy indexes) of the distribution of the marginal outcome variable is affected by an infinitesimal rightward location shift in the distribution of regressors. We approximate the effect on quantiles and various inequality indicators of slightly disturbing the joint distribution of per capita and labor income and observable characteristics towards the distribution where migration is larger.

Intuitively, RIFs are constructed by adding the specific distributional statistic (ν) under consideration to its corresponding influence function (IF), which re-centers the IF on the statistic ν. The IF is a statistical tool that measures the sensitivity of a certain distributional statistic of interest to outliers in the sample.[9] The use of the RIF allows to express the statistic ν as an expectation and to use the Law of Iterated Expectations. Following the methodology of Firpo et al. (2009), we assume a linear model, $\mathbb{E}[\mathsf{RIF}(Y;\nu)|X] = X'\beta$.

Specifically, we estimate the following equation:

$$\mathsf{RIF}(y_{idt}, \nu_Y) = \beta M_{dt} + X'_{idt}\delta + \omega_d + \pi_t + \theta_m + \mu_{idt} \tag{2}$$

Where:

$$\nu_Y : \{\text{Quantile, Gini Coefficient, Atkinson Index, Entropy Index}\}$$

In short, when estimating the effect of an explanatory variable by considering any distributional statistics, we are basically estimating the effect of a marginal change in our explanatory variable (in our case migration) on ν. From equation (2) we have that y_{idt} is the outcome variable of individual i living in Colombian department d in year-month t. Our variable of interest is M_{dt} which represents the share of Venezuelan immigrants relative to the local population in each department-year-month. We consider as Venezuelan immigrants those individuals in the GEIH who reported being born in Venezuela. X_{idt} is a vector of individual variables including age, squared age, sex, years of education, marital status and the relationship to the head of household of each individual i; ω_d, π_t and θ_m are department, year and month fixed effects, respectively. Finally, μ_{idt} is the error term. We cluster standard errors at departmental level to account for potential serial correlation between individuals in the same department over time. Considering the small number of clusters, we estimate more conservative p-values by implementing the wild bootstrap-t method (Cameron et al., 2008; Webb, 2013); nonetheless, results remain virtually unchanged.

Our parameter of interest, β, captures the marginal average effect of an increase in the share of immigrants of 1 percentage points (p.p.) on ν considering the RIF equation (2). Given that the location of Venezuelan immigrants in each Colombian department is not random we address this endogeneity concern by implementing an instrumental variable approach. The instrument for M_{dt} is a well-known enclave instrument that has been used in several papers analyzing episodes of forced migration (see, for instance, Del Carpio and Wagner, 2015; Morales, 2018; Caruso et al., 2019). This instrument exploits the fact that given the forced nature of the migration, the location of Venezuelan migrants was specially concentrated on Colombian departments close to the state from which the displaced person fled. Formally:

$$IV_{dt} = V_t \sum_s \frac{\alpha_s^{2011}}{K_{ds}} \tag{3}$$

[9] For example, the IF of the mean is given by $Y - \mu$. It is worth noting that there is a different IF for each distinct statistic. This function is not bounded, which means that "contaminating" the sample with observations that are far from the mean will have a greater influence on this statistic than observations closer to it (i.e., the mean is not a robust measure of central tendency). Consequently, the RIF of the mean is given by Y.

where V_t is the stock of Venezuelan immigrants living in Colombia in year-month t and provides time variation to our IV. This component is not correlated to the differences in the share of Venezuelans across Colombian departments given that the sudden increase in the inflow of Venezuelans between 2015 and 2019 was due to the socio-economic crisis, a push-factor, occurring in Venezuela. Furthermore, α_s^{2011} is the share of Venezuelans living in the Venezuelan state s according to 2011 Venezuelan census (pre-crisis) and K_{ds} is the driving-distance in kilometers between Colombian department d and Venezuelan State s.[10]

The intuition behind the instrument is that those Colombian departments located near to the border with Venezuela and, specifically, near to Venezuelan states with historically high population density, are expected to face higher immigration than those departments located far away from the borders. Figure A.2 shows the first-stage correlation between the enclave instrument and the share of Venezuelan immigrants which appears to be strong, supporting the relevance condition of the instrumental variable approach proposed in this paper. The instrument is significant at the one percent significance level in every specification that we estimate and the F-statistic is well above the standard levels. In Section 7 we perform some additional checks to ensure the internal validity of our empirical strategy.

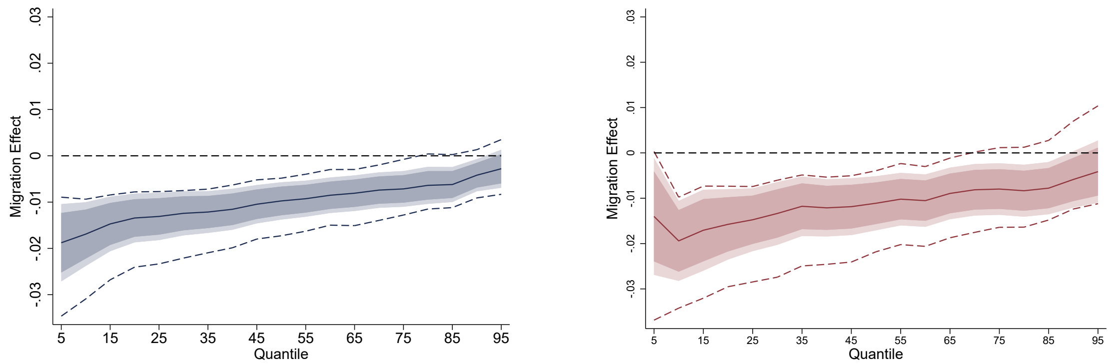
4.2 Results: The effect of immigration on natives' income

Income distribution. The average effect of immigration on total and labor income is negative and statistically significant, as shown in Figure B.1 of Appendix B. However, this average effect hides heterogeneities across the per capita family income (PCFI) and the per capita labor income (PCLI) distributions. We estimate the Unconditional Quantile Partial Effect (UQPE) for each ventile of the native family and labor income distributions. Our results are shown in Figure 2. As can be seen, the average negative effect of immigration shown in Panel (a) of Figure B.1 seems to be concentrated mainly in the left tail of the natives' PCFI distribution. Our estimates indicate that, once we control for individual characteristics and the non-random location pattern of Venezuelan immigrants through our IV strategy, the negative effect of those below the 25th percentile of the income distribution almost doubles that of those on the right tail. The pattern for the labor income distribution –Panel (b)– is analogous to the one found for the PCFI.

[10] Driving-distance is estimated by implementing Stata command *georoute* written by Weber and Péclat (2017).

Figure 2: Unconditional Quantile Partial Effects of Immigration on Native Per Capita Family Income and Per Capita Labor Income

(a) Per capita family income (b) Per capita labor income



Notes. Each solid line represents the estimated UQPE according to the equation (2) for each ventile of the corresponding per capita income. The estimates sample corresponds to native individuals. The dark and light areas are the 90% and 95% confidence intervals, respectively. Standard errors were clustered at the departmental level. The dashed line represents the 95% confidence interval with cluster-robust wild-bootstrap test. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects.
Source: Own elaboration based on data from DANE.

Four facts suggest that the entire negative effect of Venezuelan forced migration on total income is due to a regressive impact of immigration on the labor market for native workers. Firstly, labor income represents approximately 80% of total individuals' income according to GEIH in our sample period. Also, the negative effect on labor income appears to be basically the same compared to total income (See Figure B.1 of Appendix B). Additionally, previous studies have found that Venezuelan immigration negatively affected native workers' wages, especially those of low-skilled and informal workers (Caruso et al., 2019; Peñaloza-Pacheco, 2019). Finally, Figure B.2 of Appendix B strengthens this argument by discarding alternative sources of income: the UQPE for the other income sources (transfer and capital income) show no clear negative effect or regressive pattern. This goes in line with the fact that Venezuelan immigrants may have put greater pressure on the wages of natives, affecting them negatively due to higher levels of competition between native and immigrant workers.

Finally we consider the two potential sources that might explain the negative effect on wages: hourly wages and hours worked. Figure B.3 of Appendix B shows that the regressive effect comes entirely from hourly wages. Those that earn below the 50th percentile of the hourly wages distribution suffered to a greater extent the negative effect of Venezuelan migration compared to those at the right end of the distribution. Instead, when considering the number of hours worked, it is not possible to identify any negative effect.

Inequality. Based on the results presented so far, we know that Venezuelan immigration negatively affected the labor income of the lowest paid individuals (and in particular, those with the lowest hourly wages), who are expected to be the poorest in the income distribution. These effects could have affected the income distribution among native individuals by increasing inequality due to the relative worse situation of those with lower incomes compared to the native population on the right side of the income distribution. In order to test for these inequality regressive effects, Table 1 shows RIF-regression estimates of equation (2) with inequality indicators such as the Gini coefficient, Atkinson index and Entropy index as outcomes.[11]

Several insights emerge from our results. First, the OLS estimates appear to be a lower bound of the actual effect of immigration on inequality. Once we control for the non-random pattern of allocation of Venezuelan immigrants in Colombian departments by implementing an IV strategy, our estimated coefficients almost double those of the OLS estimates. This result is expected given that it is reasonable that Venezuelan immigrants choose departments where the social situation of natives is better and, therefore, if we do not control for this negative correlation between the migratory pattern and inequality our estimates could be biased downward. Second, our estimates indicate that, regardless of which inequality indicator is considered, the Venezuelan exodus increased inequality: for instance, a 1 p.p. increase in the share of Venezuelan immigrants increased the Gini coefficient by 0.002 points.

Doing some back of envelope calculations, on average the proportion of Venezuelan immigrants for each of Colombia's departments increased by approximately 3 p.p., which translates into an average Gini coefficient rise of 0.006 points, which is very close to the average annual reduction of the same coefficient at the national level during the 2013-2017 period. This 0.002 point effect on the Gini coefficient is also close to a 0.4% increase relative to the national Gini coefficient in Colombia before the Venezuelan exodus (2013).[12]

[11] The Gini coefficient weights individuals equally in terms of their relative position across the wage distribution. This means that there is no greater weight for Dalton-Pigou income transfers farther from the mean of the distribution than for those closer to the average (conditional on leaving the ranking of individuals in the distribution unchanged). The Atkinson indices measure the percentage of income that individuals are willing to sacrifice to achieve an equal wage distribution. The calculation uses a welfare CES function where the weighting assigned to each individual in the distribution depends on the elasticity of substitution coefficient ε. If this is equal to zero, the function is utilitarian, but as the coefficient grows, the welfare function tends to become rawlsian (i.e., more averse to inequality, so there is greater weighting of transfers that occur between individuals at the extremes of the distribution). The entropy index is a measure of redundancy in data, i.e. data compression. The measurement of inequality of this index depends on its parameter α which regulates the weight given to distances between incomes at different parts of the income distribution. For a large α the index is especially sensitive to the existence of large incomes, whereas for a small α the index is especially sensitive to the existence of small incomes.

[12] See Table A.2.

Table 1: Effect of immigration on inequality

	Gini	Atkinson (0.5)	Atkinson (1)	Entropy (0)	Entropy (1)
Share of Immigrants (OLS)	0.001**	0.001**	0.001**	0.002**	0.002*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
	[0.026]	[0.020]	[0.010]	[0.014]	[0.050]
Share of Immigrants (IV)	0.002***	0.002***	0.003***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	[0.012]	[0.008]	[0.004]	[0.004]	[0.016]
F-statistic	141.68	141.68	141.68	141.68	141.68
Number of Departments	24	24	24	24	24
Observations	4,860,555	4,860,555	4,860,555	4,860,555	4,860,555
Department FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Economics controls	Yes	Yes	Yes	Yes	Yes

Notes. Each column represents the estimated coefficient of the share of Venezuelan immigrants relative to native population on each column outcome for the period 2013-2019 using equation (2). The estimates sample corresponds to native individuals. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects. Clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level.
Source: Own elaboration based on data from DANE.

Our estimates suggest that the effect of forced Venezuelan migration in Colombia increased inequality among native individuals. These impacts were mainly driven by the fact that Venezuelan immigrants competed particularly with workers at the bottom of the labor income distribution, which are expected to be those employed in low-skilled and more routine jobs. These effects, however, are puzzling considering that, as shown in Table A.1, Venezuelan immigrants have at least as the same skill level compared to Colombians, so if greater competition with native workers was expected, it should be primarily among the highly skilled.

In the following sections we empirically show that Venezuelan immigrants, regardless of their skill level, have downgraded in the Colombian labor market due to legal barriers to integrate and regularize their migratory status. Thus, they were forced to compete for low-skilled, more routine and lower-paying jobs, affecting the wages of Colombia's poorest natives and increasing levels of inequality. We will then show that once these legal barriers were reduced through the implementation of a massive amnesty program for undocumented Venezuelan immigrants, the pressure on the lower part of the labor income distribution was reduced due to a reallocation of Venezuelan workers into other segments of the Colombian labor market that better match their observable characteristics such as skills.

5 Downgrading of Venezuelan Immigrants

Downgrading of immigrants in the labor market, according to the economic literature, is the situation in which immigrant workers (in our case Venezuelan workers) are employed in jobs that are worse (in terms of wages, routine and skills) than the jobs of native individuals with the same observable characteristics such as education, experience and age (Dustmann et al., 2013, 2016).

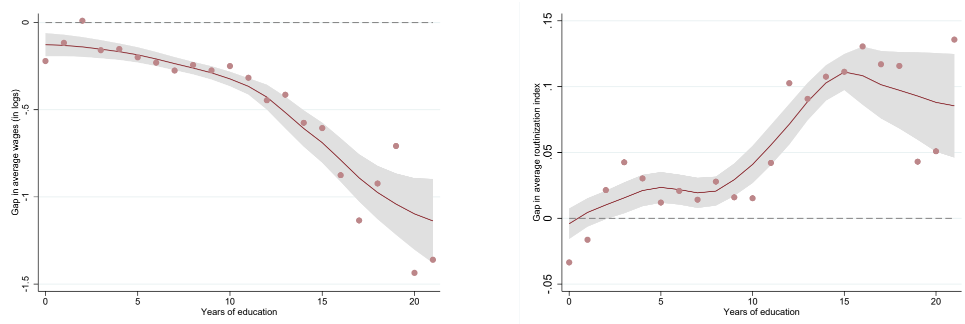
Downgrading can be caused by several reasons. On the one hand, there are informal or non-legal reasons, such as the fact that some immigrants have a different mother tongue from that of the host country or region and therefore have to spend time upon arrival to learn the language of the natives in order to work in more skilled jobs. In this case, it is expected that, once immigrants succeed in acquiring these skills, they are able to better integrate into the labor market and there will be a job upgrading. On the other hand, there are formal or legal reasons that prevent immigrants from effectively participating under the best conditions in the labor market due to barriers to formalization or restrictions that do not allow them to validate their educational credentials or to have a legal and defined migratory status. Finally, a combination of both situations can arise.

In the case of the Venezuelan exodus, immigrants are very similar to native workers (they speak the same language and have quite similar cultural backgrounds compared to Colombians), so they have no non-formal reasons to downgrade in the labor market. However, due to the lack of legal mechanisms for their regularization upon their arrival, they could not legally integrate into the Colombian economy and had to participate mainly in informal, low-skilled and routine jobs.

We propose that downgrading is the main driver of the inequality effect of the Venezuelan exodus in Colombia. Figure 3 shows the unconditional gap in terms of wages and routinization between immigrants and Colombian workers for each year of education in 2019. Both figures mirror each other. In the case of wages in panel (a), we can observe that immigrant workers earn an hourly wage that is consistently lower compared to native workers with the same years of education. Moreover, the higher the number of years of education of immigrants and natives, the larger the wage gap between the two groups: while an immigrant worker with 5 years of education earns, on average, an hourly wage that is 18% lower compared to a Colombian worker with the same years of education, this difference approaches 58% for an immigrant worker with 16 years of education compared to a native worker with the same education. The pattern in panel (b) of Figure 3 for the routinization index is the same: Venezuelan workers are employed, on average, in more routine jobs compared to native workers with the same number of years of education. Consistent with panel (a), the higher the years of education of Venezuelan and Colombian workers, the greater the gap in the routinization index.

Figure 3: Gap in wages and routinization between Venezuelan immigrants and natives in Colombia by years of education, 2019

(a) Wages (b) Routinization



Notes. Each point on the graph represents the difference in the average wage (in logs) and routinization index of immigrants and natives for each year of education. In the case of wages, a negative value means that the average wage (in logs) of immigrants is lower than that for natives for a given year of education. While, in the case of routinization a positive value means that the average routinization index of immigrants is higher than that for natives for a given year of education. The solid line was constructed from a smooth local polynomial. The gray area is the 95% confidence interval.
Source: Own elaboration based on data from DANE.

These first calculations in Figure 3 are suggestive of the presence of downgrading of Venezuelan immigrants vis-à-vis Colombian workers with the same skill level. That is, the fact that, given the years of education, Venezuelan immigrants have jobs with significantly lower wages and more routine tasks, and that this gap intensifies the more years of education they have, could indicate that they are downgrading in the labor market due to potential restrictions that make them work in the informal sector and, therefore, in less complex and worse paying jobs. In the following subsection we analyze this issue in greater depth.

Downgrading measurements. We estimate downgrading in terms of wages and routinization of Venezuelan immigrants by implementing a methodology similar to the one used by Dustmann et al. (2013, 2016). First, we estimate the following equation for Colombian workers:

$$Y^c_{ijhk} = \alpha^c_j + \beta^c_j X^c_{ijhk} + \mu^c_{ijhk} \tag{4}$$

Where Y^c_{ijhk} is the wage or the routinization index of Colombian individual i of sex j, age category h and education category k; X is a vector of variables including dummies of age and education categories (and their interactions) and department fixed effects.[13] We estimate each

[13] Age categories are (18/25), (26/35), (36/45), (46/55) and (56/64). The education categories are incomplete secondary, complete secondary, incomplete post-secondary education and complete post-secondary education.

equation for both male and female workers separately. Then, from the estimated coefficients for Colombian workers we predict the wage (routinization index) of Venezuelans from their characteristics with the following equation:

$$\hat{Y}^v_{ijhk} = \hat{\alpha}^c_j + \hat{\beta}^c_j X^v_{ijhk} + \hat{\epsilon}^v_{ijhk} \tag{5}$$

Where $\hat{\epsilon}^v_{ijhk}$ is constructed from a normal distribution of zero mean and variance equal to the residual variance of each sex-age-education category of the regressions for Colombian workers:

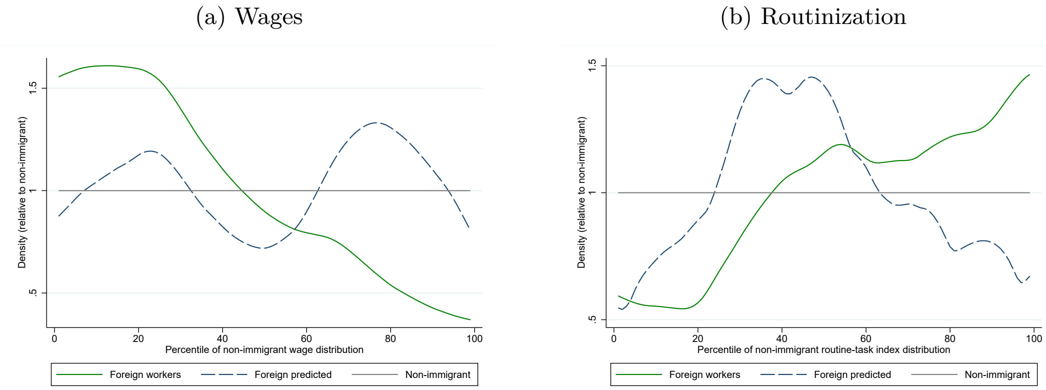
$$\hat{\epsilon}^v_{ijhk} \sim \mathcal{N}\left(0, \sqrt{\frac{\sum(\hat{\mu}^c_{ijhk})^2}{n_{jhk}}}\right) \tag{6}$$

Then, we compare the actual and predicted income or routinization index of Venezuelan immigrants. Thus, if Y^v_{ijhk} is lower (greater) than $\hat{Y}^v_{ijhk}$, this means that Venezuelans actually earn a lower wage (work in more routine jobs) than what they should do according to their characteristics under the native wage (routinization index) distribution.

Panel a (panel b) of Figure 4 shows the distribution of the wage position (routinization index) of migrants relative to the wage distribution (routinization index distribution) of natives. Both panels show the distribution for the actual and predicted wage (routinization index) of Venezuelan migrants and include the horizontal line of value equal to 1 that corresponds, by definition, to natives. For panel (a), the figure can be read as follows: a density value equal to 1.8 at the 10th percentile indicates that Venezuelans are 80% more likely to be in the 10th percentile of the native wage distribution compared to Colombians. Similarly, in panel (b) a density value close to 1.4 at the 90th percentile indicates that Venezuelan workers are 40 percent more likely to be in the 90th percentile of the native routinization distribution compared to Colombian workers, i.e., they are more likely to be in jobs with highly routine tasks.

Both panels are highly suggestive of downgrading among Venezuelan workers in Colombia. In both panels of Figure 4 we can observe that the actual wage and routinization index distributions of Venezuelan workers mirror each other: while our estimates suggest that Venezuelan workers are significantly concentrated in low-wage jobs, especially below the 40th percentile compared to natives and their predicted value given their observable characteristics, they are also heavily concentrated in jobs in the right tail of the routinization index distribution (i.e., approximately above the 60th percentile), compared to natives and their predicted value given their education, age and gender. Finally, it is worth noting that the predicted distributions in terms of wages and routinization for Venezuelan workers (dashed line in both panels) are more similar to the actual distributions of native workers (horizontal line of value equal to 1). However, immigrants are expected to be less concentrated than natives in jobs with very low routinization given their observable characteristics and more concentrated between the 20th and 60th percentile.

Figure 4: Downgrading of Venezuelan immigrants in Colombia



Notes. Both panels show the density of immigrants located in each of the percentiles of the native wage and routinization index distribution, respectively. The green line corresponds to the actual density of immigrants at each percentile; the blue dashed line is the predicted density according to equation (5). By definition the horizontal gray line represents native workers since they are equally distributed at each wage (routinization index) percentile.
Source: Own elaboration based on data from DANE.

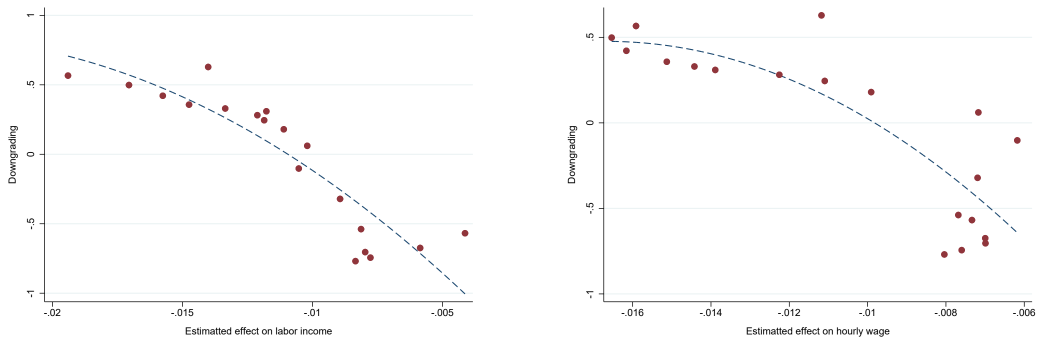
The fact that Venezuelan workers downgraded upon their arrival in Colombia and were placed in low-paying jobs due to formal barriers or restrictions in the labor market may explain the stronger negative effect on the left-hand side of the labor income distribution found above (Figures 2 and B.3). In short, when Venezuelans arrived in Colombia they tried to find a job and, due to their irregular migration status, the impossibility of working in formal (and therefore better paying) jobs and validating their educational credentials, they could only work in low paying jobs, with more routine tasks, putting additional pressure on the low-income segment of the labor market, increasing their relative labor supply, lowering wages in those jobs and having an aggregate unequalizing effect. Figure 5 shows evidence in that direction.

Each point in Figure 5 relates the UQPE for each ventile of the per capita labor income and hourly wage presented above in Figures 2 and B.3, respectively, and the gap between the actual and predicted density of Venezuelan workers for each ventile of the native wage distribution according to panel (a) of Figure 4. As can be seen, there is a negative relationship between both variables: the larger the downgrading (gap between the actual and predicted density of immigrants along the native wage distribution in Figure 4) the larger (in absolute value) and more negative is the effect of the Venezuelan exodus on the per capita labor income and the hourly wage of native workers. These relationships suggest that the greater pressure of Venezuelan immigrants on low-paying jobs due to downgrading is the main driver of the negative effect on the wages of low-income natives and, therefore, of the unequalizing effect of Venezuelan migration.

Figure 5: Relationship between downgrading and the estimated effect of migration on per capita labor income and hourly wage

(a) Per capita labor income

(b) Hourly wage



Notes. The figures relate the difference between the actual and predicted density of immigrants along the native wage distribution (the difference of the green and blue lines in Panel (a) of Figure (4) and the estimated UQPE of Venezuelan migration for each ventile of the per capita labor income distribution (Panel a) and the hourly wage distribution (Panel b).
Source: Own elaboration based on data from DANE.

Considering the information presented above, the downgrading of immigrants seems to be the driver and necessary condition for the negative effect of the Venezuelan exodus on the wages of low-wage workers and, therefore, of the strong effects on inequality. If this is the case, it might be expected that an amnesty program implemented by the Colombian government according to which Venezuelan immigrants could formalize their migratory status in Colombia and thus access better jobs, could alleviate the pressure on the informal and low paid segment of the labor market, mitigating the negative wage effects on those jobs and the effect on inequality estimated above.

6 Regularization of Venezuelan Immigrants

6.1 The amnesty program: PEP-RAMV

Considering the growing influx of Venezuelans in Colombia and their irregular situation, the Colombian government took several measures in order to integrate them and legalize their migratory situation in the country. Although Venezuelan immigrants are allowed to enter Colombia, they are only authorized to remain in the country as tourists for 180 days, period in which the tourist visa they receive upon arrival in Colombia expires; once this period is over if they remain in Colombia they become irregular.

To regularize the situation of those Venezuelans whose tourist visa had expired, the Colombian government created a migratory status known as *Permiso Especial de Permanencia (PEP)*, which functions as a temporary residence permit that allows them to work in the formal labor market and to access public services such as health and education.This PEP migratory status was first implemented in January 2017 and February 2018 in which the government was able to regularize only 182,000 immigrants whose tourist visa had expired. However, given the limited scope of these two first waves of regularization and that they were significantly endogenous to immigrants' characteristics, we do not focus on them.

In addition, between April and June 2018, the Colombian government implemented a massive and voluntary census of Venezuelan irregular immigrants known as the *Registro Administrativo de Migrantes Venezolanos (RAMV)* to measure the magnitude of the Venezuelan exodus in Colombia. This census was carried out in 441 Colombian municipalities out of a total of 1,122, particularly those municipalities with a large presence of Venezuelan immigrants, those located close to the border with Venezuela and also those that requested the implementation of the RAMV; the census was carried out in 1,109 different points spread throughout the country.

The government explicitly stated that the registration in the RAMV was not going to have any legal consequence for those Venezuelan immigrants with an irregular status in Colombia nor any benefit such as the issuance of a residence permit like the PEP. The RAMV was able to register 442,462 Venezuelan immigrants, a figure lower than the total number of Venezuelans estimated by the national government to be living in Colombia at that time (870,093 migrants). According to Bahar et al. (2021), 49.7% of the Venezuelans registered in the RAMV were women, the average age of those registered was close to 26 years, 34.7% were married or cohabiting and 52.4% were head of household. Also, on average, the registered Venezuelans had 10.5 years of education, however the educational degree of about 89% of the surveyed Venezuelans was not officially recognized by the Colombian government. 62.6% were in the labor force, 32% were informal workers, 24.4% were unemployed and only 1.1% had access to the health system. Finally, 20% were parents and the average number of children of each individual was about 0.6.

Later, before the end of the term of Juan Manuel Santos as president of Colombia during the 2010-2018 period, he unexpectedly decided to regularize those Venezuelan immigrants who registered in the RAMV through the issuance of PEPs. In order to be regularized, Venezuelans had to apply for the PEP and the only requisites were that they had to be registered in the RAMV, they had to be in Colombia in the moment in which the announce was made and could not have any criminal record or deportation order. The process was voluntary and only 63.8% of Venezuelans received a PEP out of the total registered in the RAMV (Bahar et al., 2021).

Considering this, we will use the share of Venezuelans that received a PEP relative to the departmental population as our measure of the PEP-RAMV amnesty program implementation and will evaluate how this policy affected downgrading, the presence of labor market frictions, and inequality (in the per capita family income distribution).

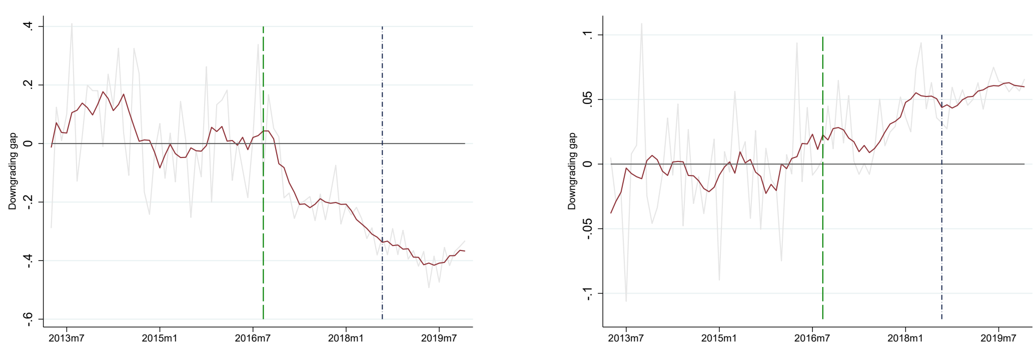
As a first approximation to this analysis, we estimate the evolution of downgrading in terms of hourly wages and routinization of Venezuelan workers over time during the 2013-2019 period. These estimates are presented in Figure 6.

Two specific moments can be highlighted in panels (a) and (b) of Figure 6: first, August 2016 (green dashed vertical line), when the borders between Colombia and Venezuela were reopened after a year of being closed due to a political crisis between the two countries; this reopening of the borders triggered the influx of Venezuelans to Colombia pushed by the Venezuelan economic and social crisis. Second, August 2018 (blue dash-dotted vertical line) when the PEP-RAMV program was implemented.

As can be seen, the downgrading of immigrants (both in wages and routinization) was around zero before the onset of the Venezuelan exodus; subsequently, between the beginning of the exodus (August 2016) and the implementation of the PEP-RAMV (August 2018) the downgrading of Venezuelan workers increased significantly along with the entry of Venezuelans into Colombia. Finally, after the implementation of the PEP-RAMV we can identify a stagnation in the evolution of downgrading in terms of wages and routinization since the moment the Venezuelan immigrants amnesty program took place. This evidence suggests that, immigrants' downgrading intensified over time and, more importantly, slowed down and stabilized when a large number of Venezuelans were regularized, which could suggest that regularization helped them to work in jobs with wages and tasks more similar to those of native workers with similar observable characteristics (education, gender and age). We will formalize the estimation of this potential effect in the following subsection.

Figure 6: Gap in wages and routinization due to downgrading in Colombia, 2013-2019

(a) Wages (b) Routinization



Notes. The gray line in panel a (panel b) of the figure shows the average gap between the actual wage (routinization index) of Venezuelan immigrants and the predicted wage (routinization index) based on their characteristics according to equation (5) for each year-month in the period 2013-2019; the red line shows the 6-months moving average to eliminate the cyclical factor of the series. The vertical dashed green line indicates the time at which the re-opening of borders between Colombia and Venezuela took place; the dash-dotted blue line shows the moment at which the PEP-RAMV amnesty program was implemented.
Source: Own elaboration based on data from DANE.

6.2 Empirical strategy for estimating the effect of the amnesty program

To estimate whether the PEP-RAMV amnesty program could mitigate the downgrading of immigrants and the consequent unequalizing impact of the forced migration, we follow an instrumental variables difference-in-difference strategy.

First, we show evidence on the effect of the PEP-RAMV amnesty program on our downgrading indicators for the sample of Venezuelan migrants through the following equation:

$$y_{idt} = \beta M_{dt} + \lambda PEP_{dt} + \phi(M_{dt} \times PEP_{dt}) + X'_{idt}\delta + \omega_d + \pi_t + \theta_m + \mu_{idt} \tag{7}$$

Where the dependent variables are (i) the gap between actual and counterfactual (log) wages of immigrants ($w_{idt} - \hat{w}_{idt}$), and (ii) the gap between their actual and predicted (log) occupation's routinization index ($r_{idt} - \hat{r}_{idt}$).[14] We analyze these outcomes for the sample of forced immigrants and for those with completed college education (a sub-sample of individuals with complete university or a postgraduate degree).

The PEP_{dt} variable is equal to the interaction between an indicator variable of the program's implementation period (a dummy that takes value equal to 1 for each observation after August 2018 inclusive and 0 otherwise) and the logarithm of PEP holders (18-65 years old) per 100,000 inhabitants in the labor force for each department at the end of the program implementation.

Our main coefficient of interest is ϕ, which indicates the effect of a 1% increase in the coverage of PEP holders (per 100,000 inhabitants), given a 1 percentage point (p.p.) increase in the share of migrants (relative to the departmental labor force) on our downgrading indicators. For example, we would expect a positive sign of ϕ when our outcome is the gap in wages, indicating an actual wage increase (or a halt in the fall of migrant wages), and therefore a decrease in downgrading due to the implementation of the PEP-RAMV amnesty program. Also, the coefficient β indicates the effect of a 1 p.p. increase in the share of migrants (relative to the department's working-age population) on the wage and routinization gaps in absence of the PEP-RAMV amnesty program. Finally, the coefficient associated with the PEP variable indicates the effect that the PEP would have had in the absence of migrants (in the tables presented below we do not include it since it lacks economic significance). The rest of the variables in equation (7) are the same as the ones in the right hand side of equation (2).

If we were to observe that the PEP-RAMV had ameliorated (at least partially) the gaps generated by downgrading, it would also be consistent to find that the program allowed skilled forced migrants to sell their labor force in a skill segment more compatible with their qualifications. That is, the fact that the program has brought wages and tasks performed by Venezuelan workers closer to the values they would have taken given their characteristics might also be

[14] We define the counterfactual wage (routinization index) as the predicted wage (routinization index) of immigrants as if their characteristics were rewarded as those of natives (as if they were employed according to their characteristics). For further details, refer to Section 5.

consistent with observing an improvement in the job matching between skilled workers and skill-intensive jobs. We therefore explore a second set of dependent variables in equation (7): the probability of Venezuelan individuals to be employed in more skill-intensive jobs.

To classify a job as skill-intensive we proceeded as follows: first, based on the 2012 GEIH information (previous to the Venezuelan exodus) we calculated three measures of skill-intensity for each 2-digit economic activity according to DANE's ISIC Rev. 3 A.C. (adapted for Colombia) classification: share of skilled individuals in each economic activity,[15] mean routine task content (RTC, see Section 3.1) and mean risk of automation (a prospective index of risk of automation, proposed by Arntz et al., 2017; Brambilla et al., 2022). Once we had the skill-intensity for each economic activity we classified them as high-skill-intensive using the median as benchmark. For instance, the economic activity that according to our measures was classified as high-skill-intensive with one of the lowest RTC and the highest share of skilled workers was "IT and related activities". Then, we built our dependent binary variable that is equal to 1 if the individual was working in a job classified as high-skill-intensive and 0 otherwise.

We can further explore how the mass amnesty program eased the difficulties faced by Venezuelan migrants' to finding jobs in their skill segment. We do so through a question in the GEIH about the worker's desire to change the job she is in to improve the use of her skills or training.[16] If it is true that the PEP-RAMV allowed skilled Venezuelan immigrants to find work in a skill segment more compatible with their skills, we should see a negative effect of the PEP-RAMV reflected in this variable. Therefore, we include this variable in our set of dependent variables in equation (7) to examine a behavior that would be consistent with the downgrading mechanism that we propose is operating behind the unequalizing effects of the Venezuelan exodus. Thus, we define two binary dependent variables that take value one if (i) the individual wants to change her job, and (ii) if this desire is due to the fact that she wants to improve the use of her skills or training.

Finally, to estimate the joint effect of Venezuelan immigration and the implementation of the PEP-RAMV amnesty program on inequality, we run RIF-regressions using the specification of equation (7). So, our dependent variable is $\mathsf{RIF}(y_{idt}, \nu_Y)$, where:

$$\nu_Y : \{\text{Gini Coefficient, Atkinson Index, Entropy Index}\}$$

Which are the RIF variables of our income inequality indicators: the Gini, the Atkinson and the Entropy indexes. Then, it is expected that the sign of ϕ would be negative, indicating a mitigation on the unequalizing effect of the Venezuelan exodus due to the implementation of the PEP-RAMV amnesty program.

[15] We define an individual as skilled if she has a degree higher than or equal to completed high-school (for example, incomplete or complete college education).

[16] In particular, the questions are: Do you want to change your current job? For which of the following reasons do you want to change your job: To improve the use of your skills or training?

The regularization decisions of Venezuelan immigrants may be correlated with labor market or socioeconomic outcomes, which poses a threat to our identification strategy when analyzing the impact of the PEP-RAMV amnesty program. To be confident that the share of regularized immigrants in each department is not correlated with prior trends in our outcome variables, we run a regression on the share of regularized immigrants of each department in 2019 and year-month dummy variables, controlling for the same covariates mentioned in equation (2). The results of these estimates are presented in Figure A.6 and they show that effectively there are no specific trends in our dependent variables of interest that are correlated with the departmental share of regularized Venezuelan immigrants. Notwithstanding this check, to account for the potential arguably endogeneity of the share of undocumented migrants who received PEP status in each department, we follow Bahar et al. (2021) and instrument the PEP_{dt} variable according to the following first-stage regression:

$$PEP_{dt} = \gamma \underbrace{[R_d \times Post_t]}_{RP_{dt}} + X'_{idt}\delta + \omega_d + \pi_t + \theta_m + \eta_{idt} \tag{8}$$

where R_d indicates the average departmental number of days available to request the PEP given by the Colombian Government to Venezuelan immigrants registered in the RAMV census and $Post_t$ is a dummy variable that takes value equal to 1 for each observation corresponding to a period after the implementation of the PEP-RAMV (0 otherwise). The rest of the variables are the same as in equation (7) (the vector of individual controls and the fixed-effects). The exogeneity of the registration days variable is explained by the fact that the time that each undocumented Venezuelan immigrant had to request the PEP was exogenously assigned and depended on the form number of each immigrant when registering in the RAMV census. This exogenous strategy of allocation of the time window to apply for the PEP-RAMV was followed by the Colombian government to guarantee the distribution of the registration workload evenly over time for public employees (For more details see Bahar et al., 2021). The average number of days to request the PEP-RAMV for each department (R_d) is given by the following expression:

$$\mathrm{R}_d = \sum_{j \in K} \frac{\text{Individuals allocated to time window j}_d}{\text{Total RAMV migrants}_d} \times (\text{Days in time window j})$$

Where K represents the 22 possible time windows that could be assigned to each of the undocumented immigrants; this number ranged between 78 and 141 days. Figure A.3 in Appendix A shows that there is a strong correlation between our potentially endogenous variable and the instrument. Also, we will observe that for each regression the weak-IV F-statistic is above the usual thresholds considered in the literature (see Section 6.3). Finally, we discuss the exclusion condition in more detail in Section 7.2.

We instrument M_{dt} as in equation (2) through the enclave IV presented in equation (3). Lastly, we instrument the interaction term ($M_{dt} \times PEP_{dt}$), with the interaction of the two instruments presented ($IV_{dt} \times RP_{dt}$), where the term RP_{dt} is the instrumental variable of the PEP-RAMV independent variable (see equation 8).

6.3 Effects of the amnesty program on downgrading and inequality

Downgrading. Following the strategy depicted in Section 6.2, in Table 2 we show our estimates of the effect of the amnesty program in the downgrading of Venezuelan immigrants in terms of wages and routinization for the sample of Venezuelan-born individuals (Columns 1 and 3) and the sub-sample of high-skilled Venezuelan forced migrants (Columns 2 and 4), where we examine individuals with complete university or a postgraduate degree.

According to Table 2, the amnesty program had a mitigating effect on downgrading, especially for wages of Venezuelan workers with higher levels of education; these results are consistent with Figure 6 (it is useful to look at this image in parallel to Table 2 to quickly grasp the direction of the effects). A 1% increase in the coverage of PEP holders (per 100,000 inhabitants in the labor force), given a 1 percentage point (p.p.) increase in the share of migrants (relative to the departmental labor force) caused a 0.008% reduction in the wage gap for highly educated forced migrants (stemming from an increase of skilled Venezuelans' wages[17]).

Although this effect on the wage gap may seem small, it is not. Taking into account the values used to build Figure 1, the share of Venezuelan migrants increased after the opening of the borders by approximately 3 p.p. Moreover, taking into account the 182,000 Venezuelans regularized in the first two waves of the PEP, plus the 281,573 Venezuelans covered by the PEP-RAMV (Bahar et al., 2021), and that the number of forced migrants as of 2019 was 1.7 million (UNHCR, 2020); the amnesty program was able to regularize roughly 27% of Venezuelans. This means that there is much more room to expand the coverage of the PEP, up to 270% approximately. Furthermore, the finding that the effect is stronger and statistically significant for the wages of the most educated Venezuelan workers is in line with the fact that these workers are those whose relative gain from regularization is stronger, considering that they are the workers who face the strongest downgrading in terms of wages and routinization given their observable characteristics.

As for the effect on the routinization gap, although it is not statistically significant, the direction of the signs of the coefficients are consistent with a reduction in the gap between the routine content of the tasks performed by Venezuelan forced migrants in their occupations and the content of the tasks they should perform if they were employed according to their

[17] The effect of the amnesty program on the wage gap can be decomposed between the effect on wages and the effect on predicted wages. As shown in Table A.3 of Appendix A and as expected, the effect on counterfactual wages is not significant, yet the coefficient of the interaction between the share of migrants (M_{dt}) and the number of PEP-RAMV recipients (PEP_{dt}) on actual wages is positive and significant, even after recalculating p-values through the wild bootstrap-t method.

observable characteristics.[18]

Table 2: Effect of the amnesty program on downgrading

	Wage gap		Routinization gap	
	Total	High-skilled	Total	High-skilled
Share of Immigrants	0.000	-0.067	-0.010	0.018
	(0.019)	(0.040)	(0.010)	(0.030)
	[0.990]	[0.100]	[0.470]	[0.606]
Share of Immigrants × PEP	0.000	0.008**	0.000	-0.003
	(0.001)	(0.003)	(0.001)	(0.002)
	[0.720]	[0.024]	[0.944]	[0.174]
F-statistic	81.46	79.46	81.46	79.46
Number of Departments	24	24	24	24
Observations	14,014	1,875	14,014	1,875
Department FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes

Notes. Each column represents the coefficient of a regression of the difference between the actual wage (routinization index) and the predicted value of the same variable according to equation (5) and the share of Venezuelan immigrants relative to native population for the period 2013-2019 as was shown in equation (7). The estimates sample in columns "Total" corresponds to Venezuelan immigrants and in columns "High-skilled" to high-skilled Venezuelan immigrants. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects. Clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level. Source: Own elaboration based on data from DANE.

Labor Market Frictions. Given that the amnesty program would seem to have had a mitigating effect on downgrading, it would be consistent with the unequalizing mechanism proposed in this paper to also observe an improvement in the probability of Venezuelan migrants to work in sectors more compatible with their skills. In other words, as the program narrowed the downgrading wage gap, it would also mean that the PEP-RAMV would have eased the pressure Venezuelans exerted on the low-skilled segment of the labor market. If this were true,

[18] It is worth noting that the p-value of the coefficient associated to the high-skilled Venezuelan migrants routinization gap (Column 4, interaction panel) is 0.108. In line with this, in Appendix Table A.3 the amnesty program would appear to have a mitigating effect on observed routinization in skilled migrant occupations that is not strong enough to translate into a reduction of the gap variable (again, and consistently, the effect of the amnesty program on the predicted routinization index is not statistically significant).

given that the individuals most affected by downgrading were those Venezuelans with higher skills, they should now be able to work in higher-skilled (or less routine) sectors.

We assess this possibility in Table 3 where we present the effect of the amnesty program on the probability of employed Venezuelan workers to work in a skill-intensive sector. In general, three patterns emerge that remain robust regardless of the skill-intensity measure that we consider to determine whether an economic activity is skill-intensive or not. First, all the effects found in the table are significant for the most skilled Venezuelan workers, consistent with the fact that this is the group of workers that downgraded the most due to the exodus of forced migrants.

Second, in absence of the amnesty program, the Venezuelan exodus would have had a negative effect on the probability of migrants getting a job in skill-intensive sectors: a 1 p.p. increase in the share of migrants (relative to the departmental labor force) would have reduced the probability of getting a skill-intensive job for high-skilled Venezuelans by 3.8 p.p. (Column 2, where we defined a sector as skill-intensive through the pre-exodus median of the share of workers with more than a high school education).

Finally, for skilled Venezuelan immigrants there is a positive effect of the amnesty program on the probability of working in a skill-intensive job: for instance, a twofold increase in the coverage of PEP holders (per 100,000 inhabitants in the departmental labor force), given a 1 p.p. increase in the share of migrants (relative to the departmental labor force) increases the probability of working in a skill-intensive sector by 41.1 p.p. for high-skilled forced migrants (Column 2, interaction row).

Table 3: Effect of the mass amnesty program on the probability of working on skill-intensive job

	Skill share		Routine Task Content		Risk of Automation	
	Total	High-skilled	Total	High-skilled	Total	High-skilled
Share of Immigrants	0.005	-0.038**	0.007	-0.038***	0.004	-0.046***
	(0.007)	(0.017)	(0.008)	(0.013)	(0.005)	(0.013)
	[0.511]	[0.092]	[0.413]	[0.034]	[0.491]	[0.006]
Share of Immigrants × PEP	0.063	0.411**	0.040	0.442***	0.062	0.488***
	(0.051)	(0.152)	(0.059)	(0.110)	(0.051)	(0.101)
	[0.236]	[0.038]	[0.559]	[0.020]	[0.244]	[0.002]
F-statistic	81.46	79.46	81.46	79.46	81.46	79.46
Number of Departments	24	24	24	24	24	24
Observations	14,014	1,875	14,014	1,875	14,014	1,875
Department FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Each column represents the coefficient of a regression of the probability of a Venezuelan worker to be in a skill-intensive job as explained in subsection 6.2 and the share of Venezuelan immigrants relative to native population for the period 2013-2019, according to equation (7). The estimates sample in columns "Total" corresponds to Venezuelan immigrants and in columns "High-skilled" to high-skilled Venezuelan immigrants. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects. Robust clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level.
Source: Own elaboration based on data from DANE.

These two results on the effect of the amnesty program on downgrading and the probability of working in a skill-intensive job presented so far are consistent with the mechanism proposed in this paper of the unequalizing effect of the Venezuelan exodus in Colombia. According to our hypothesis, the fact that there were formal frictions in the labor market that impeded Venezuelan workers to formally integrate in the Colombian labor market, generated an excess of pressure on the left tail of the Colombian income distribution causing an increase in inequality. However, once the PEP-RAMV program was implemented, it allowed skilled Venezuelan workers to validate their educational degrees and certifications and compete in the high-skilled sector of the Colombian labor market, closing the gap between their predicted and actual wage and routinization index according to their observable characteristics and increasing the probability of working in skill-intensive jobs.

Consistent with our hypothesis, also in Table A.4 of Appendix A, we show that the implementation of the amnesty program reduces the probability that a Venezuelan worker would want to change jobs; this reduction is driven by a drop in the desire to change jobs because the worker perceives that her skills or training are being underutilized. In other words, this would seem to indicate that the amnesty program causes a better match between the skills (or training) of the forced migrant worker and the job in which she is employed.

Inequality. The reduction in downgrading and labor market frictions, therefore, could have reduced the pressure on the less-paid segment of the wage distribution in Colombia and could have had an equalizing effect in the country. In line with this hypothesis, in the following table we show that these effects of the amnesty program actually seem to translate into an equalizing effect on the distribution of per capita family income of native individuals. To estimate this effect we consider as outcome variables the same inequality indicators introduced in Table 1. The results of the joint effect of immigration and the amnesty program on inequality are shown in Table 4.

Table 4: Effect of immigration and the mass amnesty program on inequality

	Gini	Atkinson (0.5)	Atkinson (1)	Entropy (0)	Entropy (1)
Share of Immigrants	0.003***	0.003***	0.003***	0.005***	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
	[0.018]	[0.018]	[0.020]	[0.016]	[0.028]
Share of Immigrants × PEP	-0.017**	-0.015**	-0.016	-0.027*	-0.050**
	(0.008)	(0.007)	(0.010)	(0.015)	(0.021)
	[0.056]	[0.054]	[0.094]	[0.084]	[0.052]
F-statistic	29.75	29.75	29.75	29.75	29.75
Number of Departments	24	24	24	24	24
Observations	4,860,555	4,860,555	4,860,555	4,860,555	4,860,555
Department FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes	Yes

Notes. Each column represents the coefficient of a regression of an inequality index on the share of Venezuelan immigrants relative to native population for the period 2013-2019 and the PEP implementation variable according to equation (7). The estimates sample corresponds to native individuals. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects. Clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level.

Source: Own elaboration based on data from DANE.

Two important observations emerge from the results of Table 4. First, the unequalizing effect of Venezuelan immigration remains robust to the inclusion of the PEP-RAMV variable (with coefficients very similar in magnitude as those found in Table 1). Second, we estimate a negative effect of the amnesty program on inequality, regardless of the inequality indicator used as dependent variable in our RIF-regressions. For example, our estimates indicate that a twofold increase in the coverage of PEP holders (per 100,000 inhabitants in the labor force), given a 1 p.p. increase in the share of migrants (relative to the departmental labor force), reduces the Gini coefficient, on average, by 0.017 points (which represents a 3% of the Gini coefficient in 2019).

7 Alternative mechanisms and internal validity

In this section we discuss the internal validity and potential concerns regarding our identification strategy as well as plausible alternatives to the mechanisms proposed in this paper.

7.1 Alternative mechanism: the elasticity of substitution between natives and migrants within skill segments

We found that the large refugee inflow of Venezuelan migrants negatively affected the lower tail of the natives' income distribution despite the fact that immigrants were relatively as skilled as Colombian workers. Following Monras et al. (2021), this result can be thought in a framework in which the Colombian labor market is segmented with various labor types. At an upper level, a high-skilled segment, and a low-skilled one that are imperfect substitutes in production. In the first one there are only formal workers, while in the low-skilled one there are formal and informal workers (also imperfectly substitutable to employers). Since Venezuelan skilled immigrants without a work permit cannot sell their labor force on the high-skilled segment, they are forced to downgrade and work informally. This constrained choice set for immigrants generates an additional pressure in the lower-paid segment of the labor market explaining the unequalizing effects of the Venezuelan exodus found in this paper. In this framework, the mass amnesty program eases the barriers faced by immigrants which is consistent with the mitigating result of the program in terms of downgrading and inequality.

However, one might think in an alternative setting in which, compared to industries with skilled workers, industries with less skilled workers exhibit a higher substitution between natives and migrants due to lower training costs and easier interchangeability of employees (Orrenius and Zavodny, 2007). In other words, the degree of competition between high-skilled Colombian workers and high-skilled migrants may be weaker than between low-skilled natives and immigrants.[19] If this was the case and the low elasticity of substitution between skilled native

[19] Examples supporting this alternative hypothesis have been found in the economic literature. For instance, Orrenius and Zavodny (2007) for the U.S. find that an increase in the fraction of foreign-born workers does not affect the wages of natives in highly educated occupations. In contrast, they find detrimental wage effects of immigration in low-skilled occupations. Imperfect substitutability between highly educated immigrants and natives, indicating that the competition between high skilled workers is very small has also been found by Peri et al. (2015) and Peri and Sparber (2011).

workers and skilled immigrants was mainly explained by other factors different that the legal ones like the absence of a regularization framework, it is expected that the implementation of an amnesty program like the PEP-RAMV not to have a positive effect on the probability of immigrants to work in skilled intensive jobs and to upgrade in the labor market. However, in our estimates, we find that actually the amnesty program had a significant effect on reducing downgrading and increasing the probability of getting a high-skill job, which goes in line with the fact that the main factor explaining the downgrading of workers and therefore the over-pressure in the low-tail of the wage distribution among Colombian workers, was the legal barriers to integrate formally in the economy.

7.2 Internal validity of the IV identification strategy

Enclave instrument. Goldsmith-Pinkham et al. (2020) decompose the Bartik-type 2SLS estimator into its "shift" part and its "share" part: the estimator can be broken down into a weighted sum of just-identified separate instruments represented by each local share. Thus, while the shares can be understood as instruments, the common national shock functions as a weight matrix that shifts the share effects. Therefore, in settings such as ours where the strategy is based on differential exposure to a common shock, identification relies on the exogeneity of the shares.[20] More precisely, in cases such as the one we study in this paper, where there is a pre-shock period, the empirical strategy is equivalent to a difference-in-differences setting. Thus, testing whether the shares of differential exposure to the common shock also explain differential trends in our outcomes previous to the shock is vital to build credibility in our strategy.

Our weighted distance to Venezuela is a shift-share instrument. The "share part" is built from the product between (i) the inverse of each pairwise distance between Colombian departments and Venezuelan states, and (ii) the population density in each Venezuelan state according to the 2011 Census. These distance-density shares of 2011 (pre-shock) measure the differential exposure to the post-2015 common national Venezuelan exodus. Still, the effects we found due to the massive forced immigration of Venezuelans could be partly driven by changes that occurred at the departmental level prior to the arrival of the displaced. Then, we have to check for endogenous pre-exodus mechanisms that are correlated with both distances and our outcomes (inequality, downgrading or any other result of our research) in order to provide evidence that differential exposure to national arrival of displaced persons has identifying power. To this end, following Goldsmith-Pinkham et al. (2020) suggestion, we test for parallel-trends to alleviate the concern that our results are driven by pre-existing differential trends in our outcomes in departments with different distances to Venezuela's most populous states (and,

[20] Although, according to Goldsmith-Pinkham et al. (2020) the consistency of the estimator depends on the shares, Borusyak et al. (2018) emphasize that under some assumptions the consistency of the estimator might also come from the shocks.

hence, different exposure to the arrival of displaced citizens from that country).

Then, to test for parallel trends, we plot the reduced-form coefficients of the average distance-density shares on our outcomes of interest for the months of the two years prior to the opening of the Colombia-Venezuela border.[21] Accordingly, we regress our outcomes of interest for each year-month against the average of the distance-density shares (i.e., $\sum_s \frac{\alpha_s^{2011}}{K_{drs}}$) interacted with year-month fixed-effects. In these regressions, we control for department fixed effects, year-month fixed effects, and for a vector of individuals' variables including age, squared age, sex, years of education, marital status and their relationship to the head of household. Figures A.4 and A.5 show the results.

We find parallel-trends prior to the opening of the borders between Colombia and Venezuela. Distance shares to the most populous Venezuelan states do not statistically predict higher inequality or downgrading in the months prior to the exodus. This evidence holds for the effects on the quantiles of per capita household income, per capita labor income and hourly wage. This supports our identification assumption that the pre-exodus shares do not predict outcomes through mechanisms other than the post-2015 immigration shock.

The key threat to the validity of any distance-based instrument is that districts that are close to the departing location may systematically differ from those further away. We are able to deal with this concern by controlling for pre-shock departmental characteristics interacted with year dummies. Specifically, to be more confident about the interval validity of our instrumental variables and that they are not correlated with historical trends explained but predetermined characteristics of each department, we follow Bahar et al. (2021) and control for a full battery of variables previous to the Venezuelan exodus.[22] The variables included are: Tax income of the departmental government in 2000, Departmental government expenditure in 2000, percentage of households with one or more unsatisfied basic need in 2000, the number of terrorist attacks in each department in 2000, the departmental per capita GDP in 2000, the hectares of coca crops in each department in 2000 and, finally, the total volume of trade (exports and imports) between each Colombian department and Venezuela in 2010 (previous to the mass exodus). To control for different trends in the outcome variables on each department explained by these predetermined characteristics of each department, we interacted these variables with year dummies. Results are presented in Tables A.5, A.6, A.7 and A.8. As can be seen, results remain virtually unchanged to the inclusion of these control variables, which support the internal validity of our strategy.

Finally, it is relevant to make a brief comment on the exogeneity of the shock (V_t in

[21] Specifically, since Goldsmith-Pinkham et al. (2020) deduces that the Bartik-type instruments are a sum of shares weighted by Rotemberg weights, these authors recommend first calculating these weights to determine which Venezuelan-state-specific exposure design gets a larger weight in the overall Bartik-2SLS estimate, and thus which state-share effects are worth testing. In our design, these weights are made explicit through the product with the population density of each Venezuelan state, so when calculating the average of what we call distance-density shares, we are already considering the most and least relevant distances.

[22] The variables were obtained from the CEDES (Universidad de los Andes).

equation 3) common to all the departments, namely, the stock of Venezuelan immigrants living in Colombia in year t month m. This component is orthogonal to the differences in the share of Venezuelans across Colombian departments given that the discrete jump in the inflow of Venezuelans between 2015 and 2019 (Figure 1) was due to events occurring in Venezuela: the macroeconomic, social, and political crisis. In short, the Venezuelan exodus and its evolution over time is mainly explained by push factors rather than pull factors of the Colombian economy that could have affected the migration preferences of Venezuelans and attracted them to settle in that country. Given this, it is plausible to assume that the time-varying component of our instrumental variable (and of our shock) is not related over time to our outcome variables.

Registration days instrument. Regarding the instrumental variable of the share of PEP holders used to analyze the effects of the amnesty program, as we mentioned before, the allocation of the number of days available for registration at each location was completely exogenous. Additionally, we provide further evidence in favor of this condition in Figure A.7, where we show the coefficients of regressions of our outcomes on interactions of year-month dummies and our R_d variable. Our estimates suggest that there is no trend over time prior to the implementation of the PEP-RAMV amnesty program that is explained by the instrumental variable, which reinforces our identification strategy.

7.3 Internal migration of Colombians

Due to several episodes of internal violence caused by illegal armed groups during the last 60 years, Colombia is characterized by having the highest number of internally displaced persons (IDPs) in the world: according to UNHCR (2020) about 8.3 million people were internally displaced in Colombia as of 2020, representing about 17% of the Colombian population.

These episodes have been extensively studied in the economic literature, and the results suggest that internal migration has had a significant negative effect on workers' wages in the receiving cities that are mainly explained by labor market rigidities. Likewise, the economic literature has also found a significant effect of internal displacement on out-migration in destination cities (See, for instance Calderón-Mejía and Ibáñez, 2016; Morales, 2018). Given this significant background, it is worth considering how the effects estimated in this paper may be affected by the internal migration of Colombians caused by the Venezuelan exodus, especially from those departments where the inflow of Venezuelans was stronger.

First, it is important to consider whether the Venezuelan exodus affected the decisions of out-migration of individuals living in those most affected departments by the Venezuelan exodus. In general, it is expected that an increase in the labor supply shock with the negative consequences in the labor market found by, for example, Caruso et al. (2019) and Peñaloza-Pacheco (2019), and in terms in inequality presented in this paper, would have increased the outflow of native people from the most affected departments to the rest of the country. Figure A.8 seems to indicate that this is the case: we can observe that, after the beginning of the

Venezuelan exodus in 2016, the share of people living in the rest of Colombia and that were living in the border departments increased. However, most of this out-migration was mainly explained by low-skilled Colombian workers, compared to high-skilled ones.

This potential out-migration effect does not pose a real threat to neither our identification strategy nor to our estimates regarding the distributional effects of the Venezuelan exodus, since in the worst case scenario it would represent a lower bound for our estimates. First, considering the effect of the Venezuelan migration on inequality, assuming that out-migration from the most affected departments is zero, then the actual labor supply shock would be higher there putting an even stronger pressure on wages. Furthermore, if out-migration is analyzed in terms of the qualification of the Colombians who might have decided to migrate internally, Figure A.8 shows that most of the individuals who migrated from the most affected departments (border departments) to the rest of the country are the low-skilled ones, indicating that in the absence of any type of out-migration, the labor supply shock in the low-income segment of the labor market would have been even greater. These two potential effects would lead to a much stronger unequalizing impact of the Venezuelan immigration than those found in this paper.

8 Concluding Remarks

Assessing the distributional impact of migration is relevant, especially in a region such as Latin America, singled out as one of the most unequal in the world (Alvaredo and Gasparini, 2015). Inequality is a top social concern, and the debate on migration usually revolves around its distributional consequences. The debate on migration extends to the policy arena. There is still a lack of consensus on the most effective policy measures that governments should consider to take advantage of the welfare gains that migration can represent and to address the potential negative effects that may arise. In this paper we estimate the distributional impact of the recent massive migration of Venezuelans into Colombia, one of the main forced migration episodes in the world and analyze how the way in which immigrants formally integrate in the host economy might affect the economic impacts of a mass exodus. By taking advantage of the geographical heterogeneity in the intensity of migration across regions, we study the impact of migration on the Colombian wage and income distributions and explore the mechanisms behind these effects. In particular, to explore the heterogeneity of the impact along the income distribution we use RIF-regressions combined with an instrumental variables approach that accounts for the non-random pattern of location of immigrants.

Despite the fact that Venezuelan immigrants are on average at least as skilled as native Colombian workers, we find that the exodus had a larger negative effect on the lower tail of the wage distribution, and hence an unequalizing effect on the wage and income distributions. These results seem to be driven by a large downgrading of Venezuelan recent migrants, who tend to earn lower wages and work in more routine jobs than natives with similar characteristics.

Finally, we take advantage of a recent large amnesty program of immigrants in Colombia and find that it helped reducing the degree of downgrading, increased the probability of high-skilled Venezuelan workers to participate in skill-intensive jobs and reduced the desire of Venezuelans employees to change their jobs due to the perception of underutilization of their skills. These facts contributed to a mitigation of the unequalizing impact of the exodus by a better employee-job matching. These results can shed light on the potential role for public policies to ameliorate the short-run negative impact of massive migrations flows on the labor market and the income distribution of the host country.

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A Appendix: Tables and Figures

Table A.1: Descriptive statistics - Colombians and Venezuelans, 2019

	Colombians	Venezuelans	Venezuelans 5 years	Venezuelans 1 year
Panel A: Socioeconomic characteristics				
Age (in years)	34.07	23.62	24.97	23.86
Sex (Man = 1)	0.492	0.499	0.496	0.483
Head of household	0.323	0.218	0.232	0.174
Socioeconomic level	2.031	1.940	1.943	1.961
In a relationship	0.414	0.434	0.465	0.401
Living in an urban area	0.773	0.878	0.886	0.906
Poverty rate	0.357	0.563	0.557	0.612
Extreme poverty rate	0.098	0.155	0.151	0.170
Working age population	0.848	0.759	0.812	0.769
Employment rate	0.565	0.631	0.632	0.578
Inactivity rate	0.314	0.199	0.210	0.212
Unemployment rate	0.102	0.145	0.148	0.202
Educational level				
Years of education	7.715	7.774	8.316	7.738
Incomplete secondary	0.562	0.500	0.530	0.507
Complete secondary	0.205	0.255	0.278	0.260
Incomplete Post-secondary	0.105	0.093	0.100	0.093
Complete Post-secondary	0.094	0.086	0.089	0.073
Panel B: Working population				
Hourly wage (in logs)	8.387	8.058	8.039	7.902
Routinization index	0.49	0.54	0.55	0.56
Hours of work per week	44.072	49.644	49.760	48.585
Economic sector				
Primary activities	0.173	0.062	0.059	0.057
Industry (low tech)	0.068	0.074	0.075	0.066
Industry (high tech)	0.050	0.040	0.040	0.037
Construction	0.066	0.117	0.119	0.113
Commerce	0.264	0.462	0.469	0.514
Utilities and transportation	0.086	0.053	0.051	0.046
Skilled services	0.091	0.047	0.045	0.039
Public administration	0.032	0.001	0.001	0.000
Education and health	0.139	0.104	0.102	0.086
Domestic servants	0.031	0.039	0.040	0.041

Source: Own elaboration based on data from GEIH-DANE.

Table A.2: Income inequality and poverty indicators - Nationwide by year

	Gini	p90p10	p90p50	p50p10	A(0.5)	A(1)
2013	0.534	11.75	3.481	3.376	0.238	0.409
2014	0.533	11.61	3.439	3.375	0.236	0.406
2015	0.517	10.62	3.283	3.236	0.222	0.386
2016	0.511	10.19	3.174	3.209	0.218	0.379
2017	0.504	9.686	3.165	3.060	0.211	0.368
2018	0.512	10.15	3.225	3.148	0.219	0.379
2019	0.521	11.13	3.298	3.376	0.226	0.391
	GE(0)	GE(1)	FGT(0)	FGT(1)	FGT(2)	Extreme Pov.
2013	0.526	0.570	0.387	0.159	0.088	0.104
2014	0.521	0.566	0.376	0.154	0.085	0.103
2015	0.488	0.528	0.374	0.150	0.082	0.100
2016	0.476	0.519	0.377	0.149	0.081	0.106
2017	0.458	0.498	0.364	0.140	0.075	0.090
2018	0.477	0.521	0.358	0.139	0.075	0.086
2019	0.496	0.535	0.363	0.146	0.080	0.101

Notes. Each indicator was constructed using nominal per capita income for each year. For the calculation of the FGT(.) and Extreme Poverty indicators, the national poverty line calculated by DANE for each year was considered. Sampling weights were used to calculate the indicators.
Source: Own elaboration based on data from DANE.

Table A.3: Effect of the amnesty program on downgrading - Gap decomposition

	Wages (total)		Wages (HS)		Routinization (total)		Routinization (HS)	
	w_{idt}	$\hat{w}_{idt}$	w_{idt}	$\hat{w}_{idt}$	r_{idt}	$\hat{r}_{idt}$	r_{idt}	$\hat{r}_{idt}$
Share of Immigrants	0.011	0.010	-0.012	0.053*	-0.005	0.005	0.033*	0.016
	(0.023)	(0.011)	(0.031)	(0.029)	(0.006)	(0.006)	(0.018)	(0.015)
	[0.656]	[0.526]	[0.670]	[0.044]	[0.384]	[0.550]	[0.170]	[0.254]
Share of Immigrants × PEP	-0.000	-0.001	0.004**	-0.003	-0.000	-0.000	-0.004***	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
	[0.880]	[0.598]	[0.080]	[0.126]	[0.684]	[0.738]	[0.004]	[0.562]
F-statistic	82.87	82.87	79.63	79.63	82.87	82.87	79.63	79.63
Number of Departments	24	24	24	24	24	24	24	24
Observations	14,014	14,014	1,875	1,875	14,014	14,014	1,875	1,875
Department FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variables considered are the following: (i) w_{idt} is the actual hourly wage of the Venezuelan workers in Colombia; (ii) $\hat{w}_{idt}$ is the predicted hourly wage of the Venezuelan workers in Colombia according to equation (5); (iii) r_{idt} is the actual routinization index of the Venezuelan worker in Colombia; (iv) $\hat{r}_{idt}$ is the predicted routinization index of the Venezuelan worker in Colombia according to equation (5). Each coefficient comes from a regression according to equation (7). The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects. Total stands for the whole sample of Venezuelan migrants. HS stands for the sample of high-skilled forcibly displaced Venezuelans (as defined in Section 6.2). Clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level.
Source: Own elaboration based on data from DANE.

Table A.4: Effect of the amnesty program on the desire to change the job due to underutilization of skills

	Change job		Improve use of skills	
	Total	High-skilled	Total	High-skilled
Share of Immigrants	-0.002	0.018	-0.007	0.018
	(0.008)	(0.015)	(0.008)	(0.014)
	[0.776]	[0.369]	[0.475]	[0.299]
Share of Immigrants × PEP	0.032	-0.349**	0.008	-0.354**
	(0.081)	(0.141)	(0.066)	(0.151)
	[0.727]	[0.040]	[0.914]	[0.070]
F-statistic	82.87	79.63	82.87	79.63
Number of Departments	24	24	24	24
Observations	14,014	1,875	14,014	1,875
Department FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes

Notes. The dependent variables are the following (i) in the first two columns the dependent variable is a dummy that takes value equal to 1 if the individual answered Yes to the following question: Do you want to change your current job?; 0 otherwise, (ii) the last two columns correspond to a dependent variable that is a dummy that takes value equal to 1 if the individual answered Yes to the following question: For which of the following reasons do you want to change your job? To improve the use of your skills or your training?; 0 otherwise. The coefficients correspond to a regression as the one presented in equation (7). The estimates sample in columns "Total" corresponds to Venezuelan immigrants and in columns "High-skilled" to high-skilled Venezuelan immigrants. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects. Robust clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level.
Source: Own elaboration based on data from DANE.

Table A.5: Effect of immigration on inequality - Additional Controls

	Gini	Atkinson (0.5)	Atkinson (1)	Entropy (0)	Entropy (1)
Share of Immigrants (OLS)	0.001**	0.001**	0.002**	0.002**	0.003*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
	[0.052]	[0.056]	[0.044]	[0.042]	[0.106]
Share of Immigrants (IV)	0.003***	0.003***	0.004***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
	[0.022]	[0.028]	[0.002]	[0.002]	[0.056]
F-statistic	119.77	119.77	119.77	119.77	119.77
Number of Departments	24	24	24	24	24
Observations	4,860,555	4,860,555	4,860,555	4,860,555	4,860,555
Department FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes

Notes.Notes. Each column represents the coefficient of a regression of inequality index and the share of Venezuelan immigrants relative to native population for the period 2013-2019 according to equation 2. The estimates sample corresponds to native individuals. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects, and also the additional controls listed in subsection 7.2. Clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level.
Source: Own elaboration based on data from DANE.

Table A.6: Effect of immigration on downgrading - Additional Controls

	Wage gap		Routinization gap	
	Total	High-skilled	Total	High-skilled
Share of Immigrants	-0.038**	-0.101**	-0.012	-0.028
	(0.017)	(0.048)	(0.013)	(0.035)
	[0.068]	[0.026]	[0.432]	[0.478]
Share of Immigrants × PEP	0.002*	0.011**	0.001	-0.000
	(0.001)	(0.004)	(0.001)	(0.002)
	[0.054]	[0.016]	[0.570]	[0.912]
F-statistic	14.16	18.53	14.16	18.53
Number of Departments	24	24	24	24
Observations	14,014	1,875	14,014	1,875
Department FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes

Notes. Each column represents the coefficient of a regression of inequality index and the share of Venezuelan immigrants relative to native population for the period 2013-2019 according to equation 2. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects, and also the additional controls listed in subsection 7.2. Clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level.
Source: Own elaboration based on data from DANE.

Table A.7: Effect of the amnesty program on the probability of working on skill-intensive job - Additional Controls

	Skill share		Routine Task Content		Risk of Automation	
	Total	High-skilled	Total	High-skilled	Total	High-skilled
Share of Immigrants	-0.001	-0.038	-0.000	-0.043***	-0.007	-0.051**
	(0.007)	(0.024)	(0.007)	(0.015)	(0.008)	(0.019)
	[0.874]	[0.116]	[0.966]	[0.004]	[0.421]	[0.012]
Share of Immigrants × PEP	0.075	0.291	0.037	0.375***	0.121*	0.543***
	(0.056)	(0.205)	(0.067)	(0.119)	(0.063)	(0.110)
	[0.178]	[0.160]	[0.601]	[0.008]	[0.122]	[0.000]
F-statistic	14.28	18.40	14.28	18.40	14.28	18.40
Number of Departments	24	24	24	24	24	24
Observations	14,014	1,875	14,014	1,875	14,014	1,875
Department FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Indidividual controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Each column represents the coefficient of a regression of the probability of a Venezuelan worker to be in a skill-intensive job as explained in subsection 6.2 and the share of Venezuelan immigrants relative to native population for the period 2013-2019, according to equation 7. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects and also the additional controls listed in subsection 7.2. Robust clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level.
Source: Own elaboration based on data from DANE.

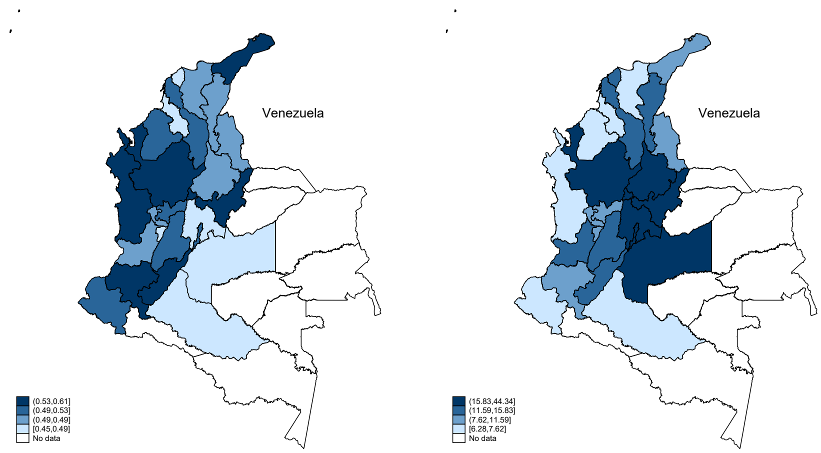
Table A.8: Effect of the amnesty program on the desire to change the job due to underutilization of skills - Additional controls

	Change job		Improve use of skills	
	Total	High-skilled	Total	High-skilled
share	-0.004	0.002	-0.004	-0.003
	(0.011)	(0.020)	(0.008)	(0.025)
	[0.754]	[0.896]	[0.585]	[0.930]
Share of Immigrants × PEP	0.053	-0.351*	0.025	-0.324
	(0.081)	(0.182)	(0.073)	(0.199)
	[0.533]	[0.044]	[0.772]	[0.100]
F-statistic	14.16	18.53	14.16	18.53
Number of Departments	24	24	24	24
Observations	14,014	1,875	14,014	1,875
Department FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Indidividual controls	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes

Notes. The dependent variables are the following (i) in the first two columns the dependent variable is a dummy that takes value equal to 1 if the individual answered Yes to the following question: Do you want to change your current job?; 0 otherwise, (ii) the last two columns correspond to a dependent variable that is a dummy that takes value equal to 1 if the individual answered Yes to the following question: For which of the following reasons do you want to change your job? To improve the use of your skills or your training?; 0 otherwise. The coefficients correspond to a regression as the one presented in equation (7). The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects and also the additional controls listed in subsection 7.2. Robust clustered standard errors at department level in parenthesis. Cluster-robust wild-bootstrap p-values at department level in square brackets. The F-statistic corresponds to the Kleibergen-Paap rk Wald statistic. ***, **, * denote significance at the 1, 5, 10 percent significance level.
Source: Own elaboration based on data from DANE.

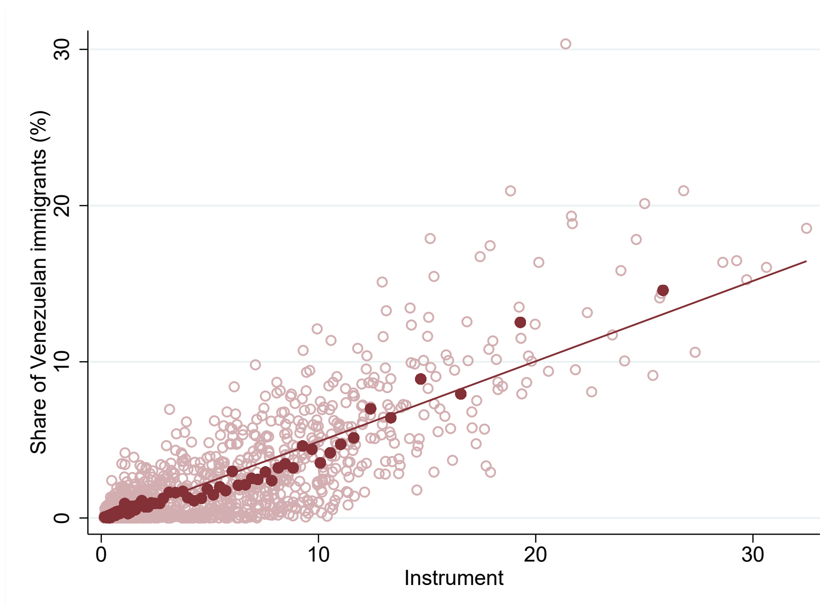
Figure A.1: Inequality and GDP, 2013

(a) Gini coefficient (b) Per capita GDP (millions COP)



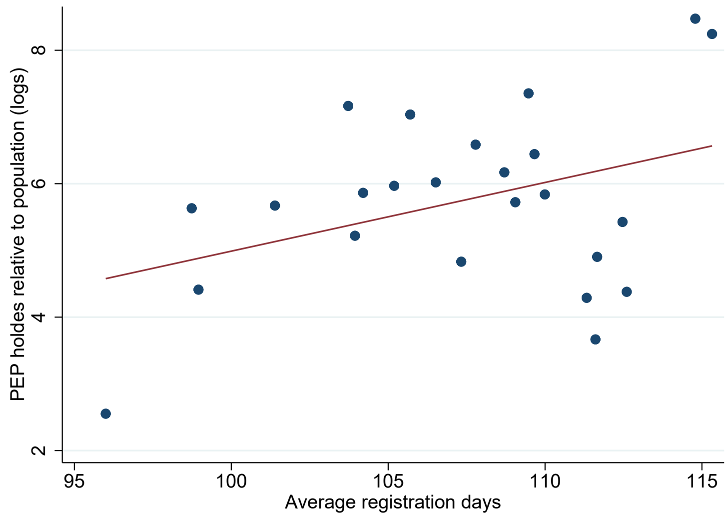
Notes. Departments with no data in the figure are mainly departments in the Amazon region with a low population density and small main cities in which data is not available. According to the last available census in Colombia (2018), population in these departments represents less than 3% of the total population in Colombia. We use survey weights to calculate the Gini coefficient.
Source. Own elaboration based on data from DANE.

Figure A.2: Relationship between the instrumental variable and the share of immigrants (%)



Notes. The figure shows the relationship between the share of immigration and the instrumental variable for each department-year-month of the sample. The darkest points correspond to the binscatters of the same variables.
Source: Own elaboration based on data from DANE.

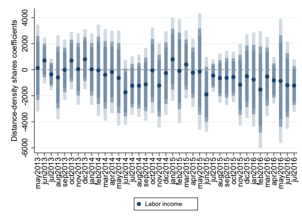
Figure A.3: Relationship between average registration days and PEP-RAMV holders by department



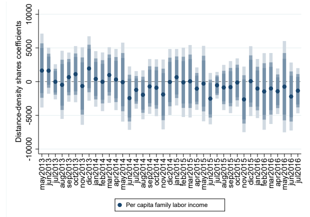
Notes. The figure shows the relationship between the share of PEP holders (in logs) per 100,000 inhabitants in the labor force and the average number of registration days available for each department of the sample. Source: Own elaboration based on data from DANE and Bahar et al. (2021).

Figure A.4: IV internal validity test (pre-trends): inequality outcomes

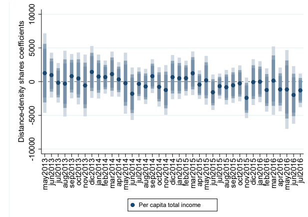
(a) Labor income



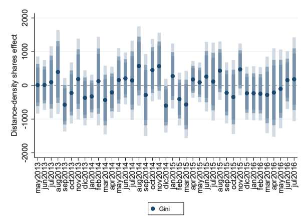
(b) Per capita family labor income



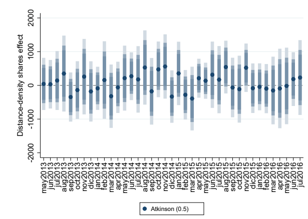
(c) Per capita total income



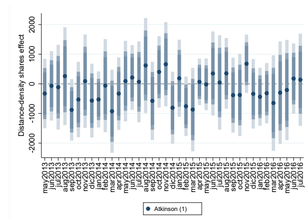
(d) Gini index



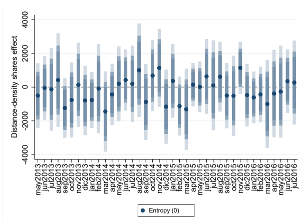
(e) Atkinson (0.5)



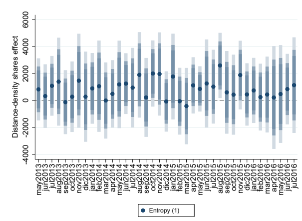
(f) Atkinson (1)



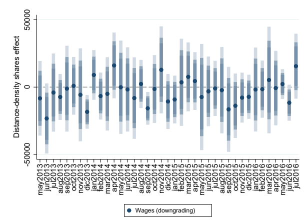
(g) Entropy (0)



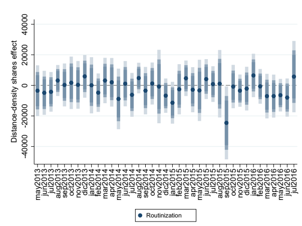
(h) Entropy (1)



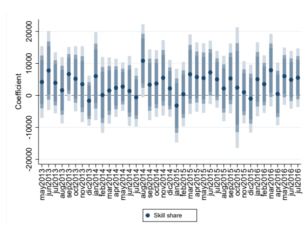
(i) Wages



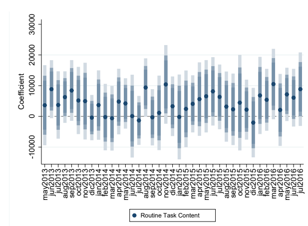
(j) Routine



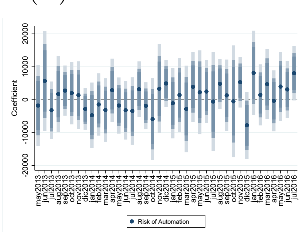
(k) Skill share



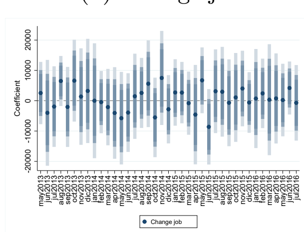
(l) Routine Task Content



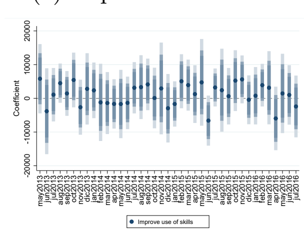
(m) Risk of Automation



(n) Change job



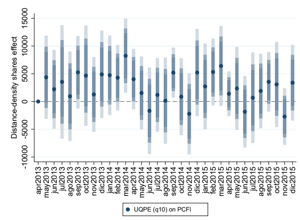
(o) Improve use of skills



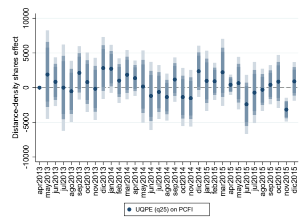
Notes. The titles above each graph show the outcome of each regression. Each dot represents the coefficient of the interaction between the average distance-density shares (i.e., $\sum_s \frac{\alpha_s^{2011}}{K_{drs}}$) for each department and year-month dummy variables. Regressions control for department, year-month fixed effects, and for a vector of individuals' variables including age (and its square), sex, years of education, marital status and their relationship to the head of household. Confidence intervals at 90%, 95%, and 99% are included. Standard errors were clustered at the departmental level.
Source. Own elaboration based on data from DANE.

Figure A.5: IV internal validity test (pre-trends): UQPEs

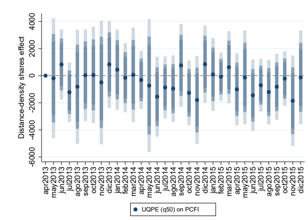
(a) UQPE (q=10) on PCFI



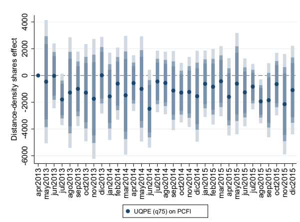
(b) UQPE (q=25) on PCFI



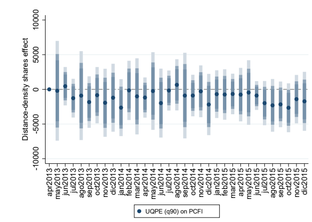
(c) UQPE (q=50) on PCFI



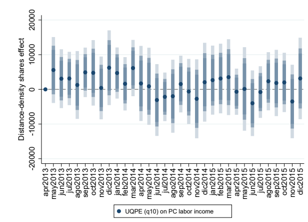
(d) UQPE (q=75) on PCFI



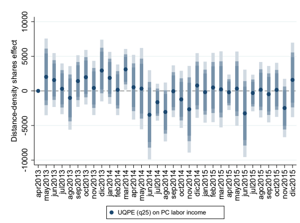
(e) UQPE (q=90) on PCFI



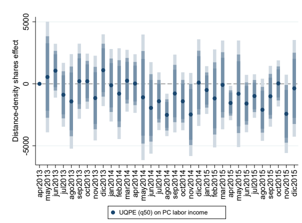
(f) UQPE (q=10) on PCLI



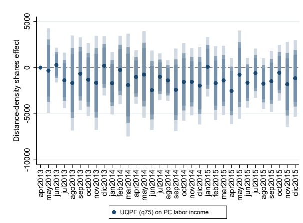
(g) UQPE (q=25) on PCLI



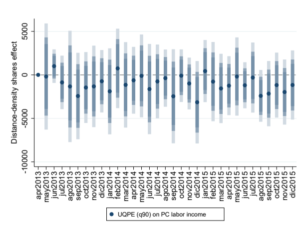
(h) UQPE (q=50) on PCLI



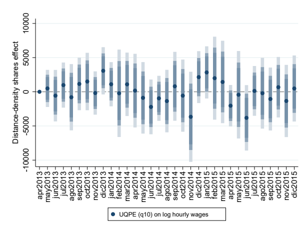
(i) UQPE (q=75) on PCLI



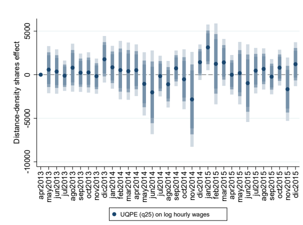
(j) UQPE (q=90) on PCLI



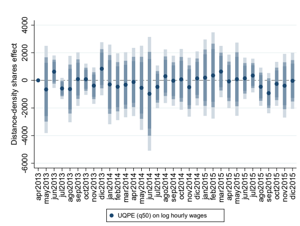
(k) UQPE (q=10) on HW



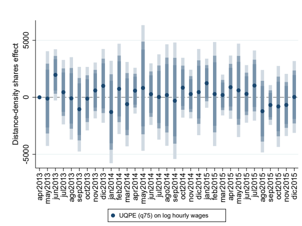
(l) UQPE (q=25) on HW



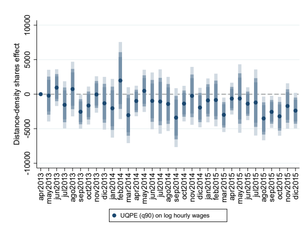
(m) UQPE (q=50) on HW



(n) UQPE (q=75) on HW



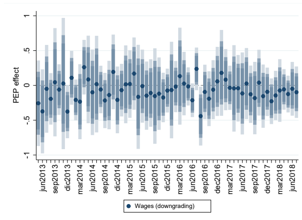
(o) UQPE (q=90) on HW



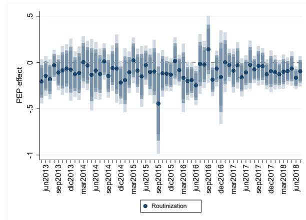
Notes. Titles above each graph show the outcome of each regression. PCFI stands for per capita family income, PCLI for per capita labor income, and HW for log hourly wages. Each dot represents the coefficient of the interaction between the average distance-density shares (i.e., $\sum_s \frac{\alpha_s^{2011}}{K_{drs}}$) for each department and year-month dummy variables. Regressions control for department, year-month fixed effects, and for the same vector of individuals' variables as Figure A.4. Confidence intervals at 90%, 95%, and 99% are included. Standard errors were clustered at the departmental level.
Source. Own elaboration based on data from DANE.

Figure A.6: PEP internal validity test (pre-trends): Inequality, downgrading and labor market friction outcomes

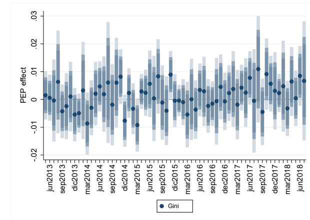
(a) Wages



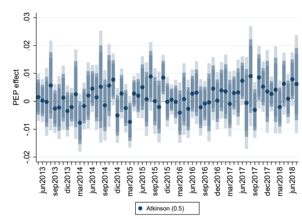
(b) Routine



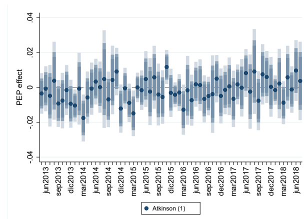
(c) Gini index



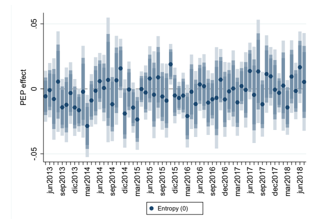
(d) Atkinson (0.5)



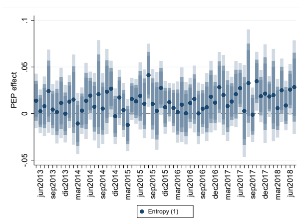
(e) Atkinson (1)



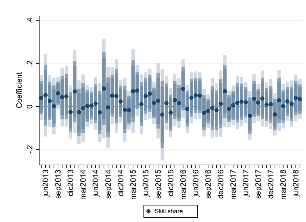
(f) Entropy (0)



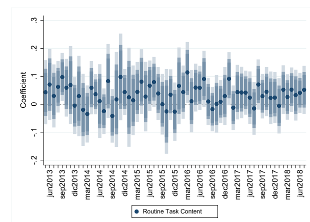
(g) Entropy (1)



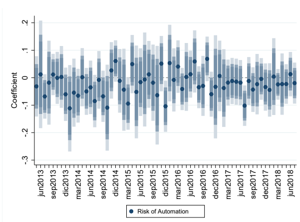
(h) Skill share



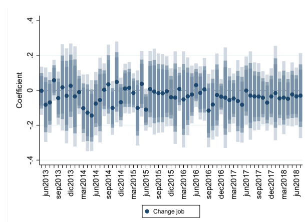
(i) Routine Task Content



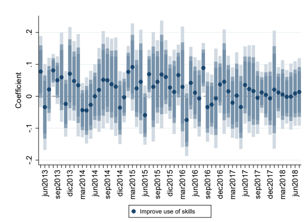
(j) Risk of Automation



(k) Change job



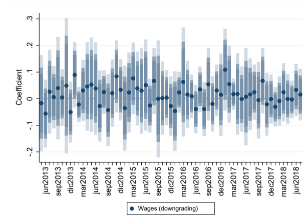
(l) Improve use of skills



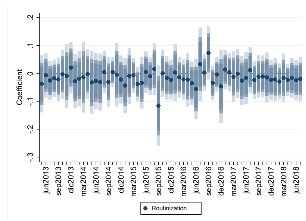
Notes. The titles above each graph show the outcome of each regression. Each dot represents the coefficient of the interaction between the share of PEP holders per 100,000 inhabitants (in logs) for each department at the end of the program implementation and year-month dummy variables. Regressions control for department fixed effects, year-month fixed effects and for the same vector of individuals' variables as Figure A.4. Confidence intervals at 90%, 95%, and 99% are included. Standard errors were clustered at the departmental level.
Source. Own elaboration based on data from DANE.

Figure A.7: Registration days instrument internal validity test (pre-trends): Inequality, downgrading and labor market friction outcomes

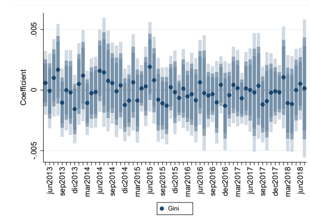
(a) Wages



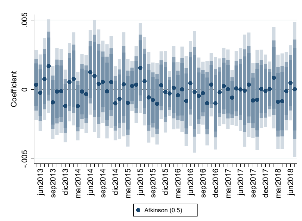
(b) Routine



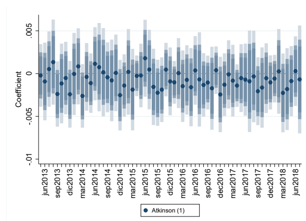
(c) Gini index



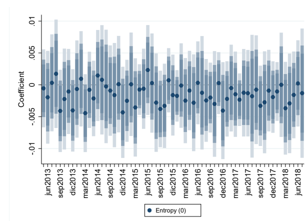
(d) Atkinson (0.5)



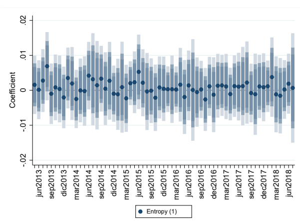
(e) Atkinson (1)



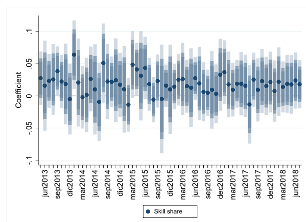
(f) Entropy (0)



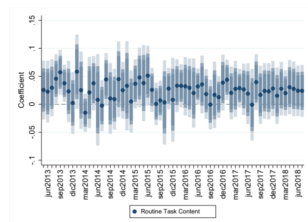
(g) Entropy (1)



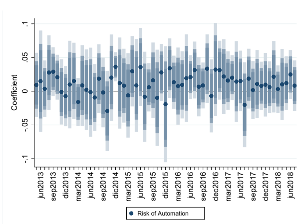
(h) Skill share



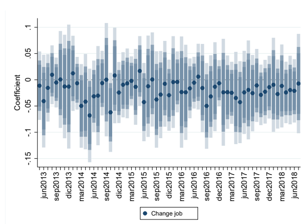
(i) Routine Task Content



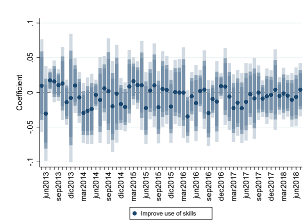
(j) Risk of Automation



(k) Change job

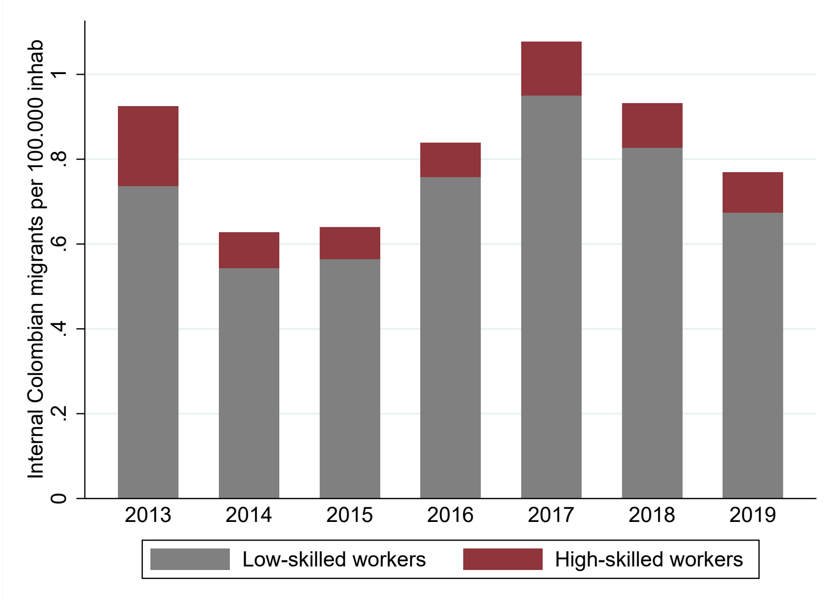


(l) Improve use of skills



Notes. The titles above each graph show the outcome of each regression. Each dot represents the coefficient of the interaction between the average number of registration days available to request the PEP-RAMV in each department (i.e., R_d) and year-month dummy variables. Regressions control for department fixed effects, year-month fixed effects, and for the same vector of individuals' variables as Figure A.4. Confidence intervals at 90%, 95%, and 99% are included. Standard errors were clustered at the departmental level.
Source. Own elaboration based on data from DANE.

Figure A.8: Internal migration in Colombia from border departments, 2013-2019



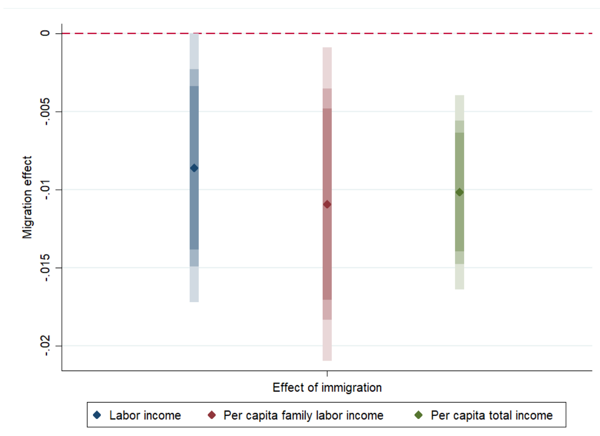
Notes. The figure shows the share of internal immigrants (per 100.000 inhabitants) who arrived during the last 12 months from the border departments relative to the local population of the rest of the country. Source: Own elaboration based on data from DANE.

B Appendix: Effect of migration on different income sources

Figure B.1 displays the effect of Venezuelan forced migration on the mean income of natives: labor income, family labor income per capita, and total income per capita. The sample for the former is composed of the native working population, while the sample for the latter two is total population. To obtain these three average results, we ran a fixed-effects regression on the outcomes just mentioned (instead of a RIF-regression), instrumenting for Venezuelan migration at the department-year level with the IV mentioned in Section 4.1.

As can be seen in Figure B.1 the average effect of immigration on total and labor income is negative and statistically significant. Our estimates indicate that a 1 percentage point (p.p.) increase in the share of immigrants relative to the departmental population reduces total and labor income per capita, on average, by 1%.

Figure B.1: Effect of immigration on income



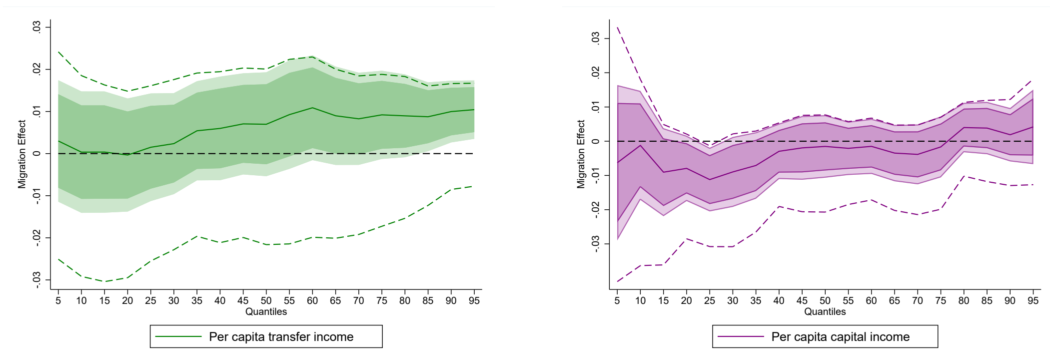
Notes. Each point shows the IV estimated effect of Venezuelan immigration on the logarithm of income for different types of sources for the period 2013-2019. The sample was restricted to individuals with positive income. The color bars represent the 90%, 95%, and 99% confidence intervals constructed using standard errors clustered at the department level. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects.
Source: Own elaboration based on data from DANE.

Figure B.2 rules out potential sources of income that could be affected by Venezuelan migration other than labor income. We consider two types of income sources: transfer income (Panel A), and capital income (Panel B). Transfer income includes revenues from assistance from other households and institutions (public and non-public). Capital income consists of revenues from interest, dividends, and rental income. As can be seen, the effect of Venezuelan migration is not statistically significant for these two sources of income along their distributions.

Figure B.2: Effect of Immigration on Native Income by Source

(a) Per capita transfer income

(b) Per capita capital income



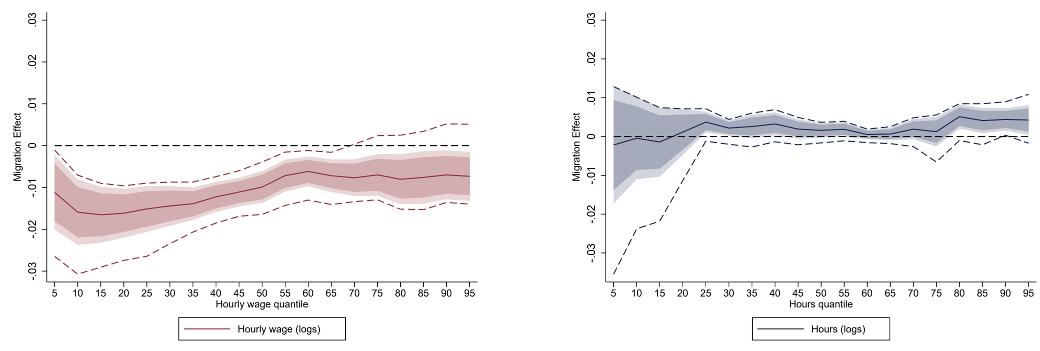
Notes. Each solid line represents the estimated UQPE according to the equation (2) for each ventile of the corresponding per capita native income. The dark and light areas are the 90% and 95% confidence intervals, respectively. Standard errors were clustered at the departmental level. The dashed line represents the 95% confidence interval with cluster-robust wild-bootstrap test. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects.
Source: Own elaboration based on data from DANE.

Finally, when considering whether the negative effect of the Venezuelan exodus on the labor income distribution comes from hourly wages, hours worked or a combination of both, economic theory puts forth two hypotheses. On the one hand, it could be possible that higher levels of competition in the labor market between natives and Venezuelan immigrants negatively affected hourly wages paid to native workers due to a greater competition in the labor market under which the increased labor supply forces nationals to be willing to work the same number of hours for a lower wage. On the other hand, this reduction in the labor income of natives, which implies an increase in the opportunity cost of working instead of consuming leisure or dedicating hours to other alternative activities, could have affected the labor decisions of native workers by making them less willing to work the same number of hours they worked before the mass exodus and, therefore, their labor income would not only have been affected by the reduction in hourly wages, but also by the lower number of hours worked.

To shed light on this dichotomy in Figure B.3 we split our UQPE estimates into two variables: hourly wages and hours worked (both in logs). Our estimates indicate that the first explanation could be the one that plays an important role in the negative redistributive effects presented in the main text; that is, increased competition in the labor market due to the incoming labor supply from Venezuelan immigrants affected the hourly wages of native workers, especially for those on the left side of the hourly wage distribution. Our estimates in panel (a) of Figure B.3 show that the negative effect on hourly wages earned by those below the 50th percentile of the distribution was significantly larger (in absolute values) compared to the negative effects of those on the right tail of the hourly wage distribution. However, when considering the number of hours worked as our outcome variable of interest, it is not possible to identify any negative effect on the number of hours worked.[23]

Figure B.3: Effect of immigration on native hourly wage and hours of work

(a) Hourly wage (logs) (b) Hours (logs)



Notes. The sample corresponds to employed individuals with non-zero income. Each solid line represents the estimated UQPE according to the equation (2) for each ventile of hourly wage in logs (Panel a) and the worked hours in logs (Panel b). The dark and light areas are the 90% and 95% confidence intervals, respectively. Standard errors were clustered at the departmental level. The dashed line represents the 95% confidence interval with cluster-robust wild-bootstrap test. The controls included in the regressions are: age, squared age, years of education, marital status, relationship to the head of household, year, month and department fixed-effects.
Source: Own elaboration based on data from DANE.

[23] The estimated effect on hours worked by native workers is different from that presented by Pedrazzi and Peñaloza-Pacheco (2020) and Caruso et al. (2019). On the one hand, Pedrazzi and Peñaloza-Pacheco (2020) analyze the effect on hours worked considering as zero those individuals who are not part of the employed population, so their effects also include the extensive margin effect of migration on employment, a variable on which Caruso et al. (2019) also finds a negative effect. On the other hand, Caruso et al. (2019) shows a positive effect on the average hours worked, however, they only analyze the 2013-2017 period, leaving out two important years in which the Venezuelan exodus intensified.