The Productivity Effects of Forced Migration:

Evidence from Venezuelan Migrants in Colombia

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Abstract[1]

Labor-supply shocks resulting from forced migrations alter skills' availability in host economies and influence firms' incentives towards formal and informal hiring, potentially affecting productivity. This paper examines the productivity effects of forced migration, using the Venezuelan exodus to Colombia as a case study. I employ a continuous difference-in-differences empirical strategy, leveraging the timing of the border reopening between Colombia and Venezuela as a source of exogenous variation. Results reveal that a one-percentage-point increase in the migration share at the industry level increased labor productivity by 7.6%. This effect was attributable to a decrease in employment and hours worked—rather than an increase in output—and was driven by the higher skill set of migrants compared to natives. Combined, these results suggest that productivity gains were derived from the replacement of less-educated natives by higher-skilled migrants. Finally, I show that productivity gains were somewhat counteracted by barriers to formality faced by Venezuelans.

JEL classifications: E24, F22, J24, J61
Keywords: Forced migration, Labor markets, Productivity, Formality, Skills

[1]This paper builds upon my previous work (Benítez-Rueda, 2022). I thank Pablo Garlati Bertoldi for his valuable guidance on this project, as well as the comments of María Paula Medina, Salvador Traettino, and Andrés Barinas.

I. INTRODUCTION

The intensification of multiple conflicts around the world is forcing a growing number of people to leave their home countries. By 2022, the count of forcibly displaced individuals had reached 108 million, doubling the figure from 2015 (UNHCR, 2023). Labor-supply shocks in host economies not only alter the skill availability but also influence firms' demand for both formal and informal workers. The resulting impact on productivity varies depending on several factors, including the magnitude of the migration influx, the educational level of migrants, their similarity to native workers and the existing regulations, and legislation that either facilitates or hinders labor market assimilation.

This paper investigates the impact of forced migration on productivity in the setting of the massive Venezuelan exodus to Colombia during the last decade. Unlike many forced migrations, Venezuelan migrants exhibited a higher average educational level than the native Colombian population. Yet, more than 70% of them were employed in the informal labor market. This produced a significant misallocation of migrant workers, as most of them were working in occupations that did not match their qualifications (Lebow, 2024; Pulido and Varón, 2023).

The expected direction of this shock's impact on productivity is not evident. On the one hand, both formal and informal firms might have seized the opportunity to hire more skilled migrants—a pool of workers previously less accessible in the informal market. Downgraded migrants might have integrated their skills into low-skilled, informal sectors, potentially enhancing efficiency.

On the other hand, the shock could have incentivized a shift towards greater firm informality. Firms may have substituted native formal workers with informal migrants, taking advantage of lower informal wages induced by the labor supply shock[2]. Recent evidence indicates that Colombian firms responded to lower informal wages by substituting formal for informal workers (Delgado-Prieto, 2022). This shift towards informality can adversely affect productivity, as informal activities are generally less productive than their formal counterparts (Ulyssea, 2020; La Porta and Shleifer, 2014; Busso *et al.*, 2012), as informal firms face greater restrictions to access credit and international markets and produce on a smaller scale to avoid being detected by the authorities.

To estimate the impact of Venezuelan migration on Colombian productivity, I built a panel dataset at the industry level matching GDP data from DANE's official National Accounts statistics and employment and migration indicators from the "Gran Encuesta Integrada de Hogares" (GEIH), the country's primary labor survey.

Because the distribution of migrants across industries was not random, the share of migrants might be endogenous to shifts in labor productivity, thus complicating the identification of a causal relationship between these variables. To empirically address this challenge, this paper uses a continuous difference-in-differences design, leveraging the exogenous timing of the border reopening between Colombia and Venezuela, the weak presence of migrants prior to this shock, and the

[2]The negative effect of Venezuelan migration on wages is well documented, especially in more informal locations (Lebow, 2022)

cross-industry variation in migration intensities that followed.

This study's primary findings show that Venezuelan migration had a positive effect on Colombian labor productivity. Specifically, a one-percentage-point rise in the migration share within an industry increased labor productivity by 7.6%, on average. Importantly, I show that this effect was driven by a reduction in employment and average hours worked rather than an increase in output, suggesting a substitution effect of native workers by migrants.

Heterogeneous effects were also explored. The positive effects on productivity were driven by industries that absorbed higher-skilled migrants. This supports the view that, probably, less-skilled natives were substituted by fewer, more-skilled migrants, boosting overall labor productivity. This is consistent with other studies that highlight some negative labor market outcomes for less-skilled natives. In particular, Venezuelan migration has implied reductions in the informal sector, self-employment and less-skilled wages (Caruso *et al.*, 2021; Bonilla-Mejía *et al.*, 2020; Penaloza-Pacheco, 2022) and reductions in participation and employment rates, particularly for less skilled natives (Penaloza-Pacheco, 2022; Bonilla-Mejía *et al.*, 2020).

Furthermore, heterogeneous effects were detected by the formality rate of migrants. In industries where a fewer portion of migrants was absorbed by the formal labor market, the positive effect on productivity diminished. This finding holds considerable policy implications. Barriers to formal employment result in an under-utilization of the migrant labor force, thereby hindering potential gains in productivity growth. The rollout of the *Permiso Especial de Permanencia* (PEP), a refugee-regularization program offered to Venezuelan migrants in 2018, significantly increased migrants' labor formalization, as shown by Ibáñez *et al.* (2022), but significant barriers remain, probably related to high payroll taxes, the unwillingness of Colombian firms to formally hire migrants and lack of information regarding formal markets' wage premium (Bahar *et al.*, 2021)[3].

This paper contributes to different segments of the migration literature. While a significant volume of studies focused on migration flows from developing to developed countries or between developed countries, such as migration flows to the United States (Peri, 2012), the European Union (Huber *et al.*, 2010; Kangasniemi *et al.*, 2012), France (Mitaritonna *et al.*, 2017), the United Kingdom (Rolfe *et al.*, 2013), Australia (Commission *et al.*, 2006), and Israel (Paserman, 2013), migratory shocks that occur between developing countries have received less attention, especially in the case of forced migrations. Understanding these dynamics is crucial, as developing economies often struggle with fragile labor institutions and expansive informal sectors.

Additionally, this paper contributes to the literature on the interplay between migrant downgrading and productivity. While previous works have primarily focused on the potential productivity gains from reallocating downgraded migrants to occupations that match their qualifications (Lebow, 2024; Pulido and Varón, 2023), This study introduces a distinct perspective. It argues that

[3]The PEP had four waves. The first two were implemented in 2017, granting regular migratory status and work permits to Venezuelans who entered Colombia through regular checkpoints and had legal immigration status. The third and fourth waves were introduced in 2018 for all Venezuelans who were registered in the Administrative Registry of Venezuelan Migrants, regardless of their migratory status (Ibáñez *et al.*, 2022)

downgrading and misallocation do not necessarily translate into a negative effect on productivity. We hypothesize that this result stems from low-skilled and informal firms having the opportunity to hire high-skilled workers. Importantly, this perspective does not conflict with the view that reducing downgrading can further remove wedges and enhance productivity

Lastly, this paper contributes to the literature studying the links between migration informality and productivity, as most studies have focused solely on labor market repercussions (Calderón-Mejía and Ibáñez, 2016; Del Carpio and Wagner, 2015), and some on production-related outcomes (Altındağ *et al.*, 2020).

The study is organized into five sections. Following this introduction, the second section delves into the context of Venezuelan forced migration to Colombia. The third section describes the construction of the panel dataset and the empirical strategy to gauge its impact on productivity. The fourth section highlights the results, and the fifth offers a conclusion.

II. VENEZUELAN FORCED MIGRATION TO COLOMBIA

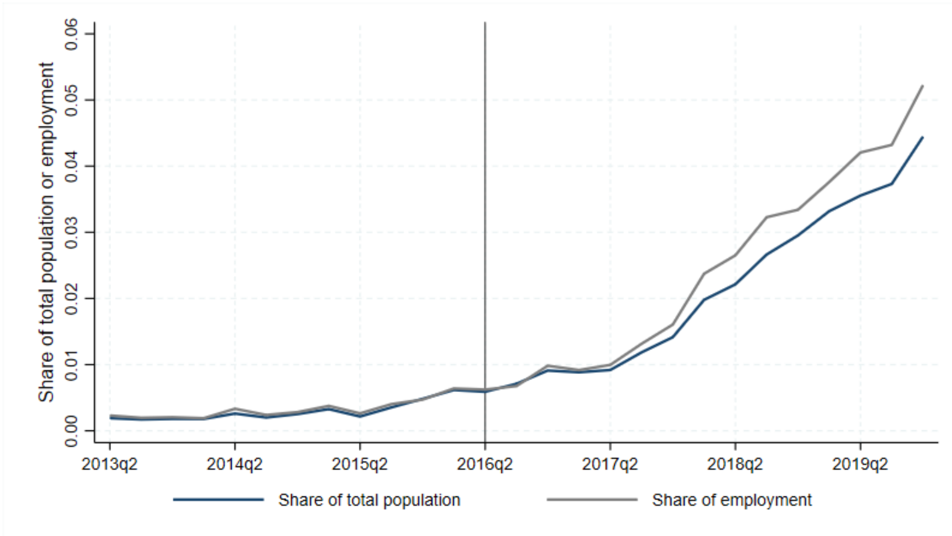
From 1999 onwards, Venezuela has experienced a significant erosion of basic economic and democratic institutions, including property rights and electoral fairness. This weakening stifled investment and growth and exacerbated Venezuela's existing vulnerabilities, especially its pronounced dependence on oil revenues. Not surprisingly, after oil prices plummeted in 2014, Venezuela entered a deep and prolonged recession, exhibiting negative GDP growth for seven straight years and an average annual contraction of roughly 16%. Amid this economic turmoil, the country grappled with severe hyperinflation, with annual inflation rates exceeding 800% between 2017 and 2020 (IMF, 2023).

This economic collapse drastically worsened the living conditions of its inhabitants, with poverty levels reaching approximately 96% (with 79% facing extreme poverty)[4]. As a result, between 2014 and 2022, more than 7 million Venezuelans (about 23% of the population) were forced to seek refuge in other nations. Colombia emerged as the primary destination for Venezuelan migrants, hosting about 2.9 million by October of 2022, which accounts for about 5.6% of its own population (Migración Colombia, 2000).

Prior to 2016, migrants from Venezuela represented about 0.2% of both the total population and employment, as shown in Figure 1. Due to diplomatic tensions between the governments of Colombia and Venezuela, the border between both countries was closed in 2015. One year later, in August of 2016, both administrations agreed to reopen the border, a decision followed by a massive entrance of migrants from Venezuela to Colombia that continued growing afterwards. In the last quarter of 2019, migrants accounted for 4.4% of the total population and 5.2% of the labor force.

[4]Based on data from the National Survey of Living Conditions (ENCOVI, by its Spanish acronym), conducted in Venezuela since 2014 by a team of professionals and academics from the Central University of Venezuela, Andrés Bello Catholic University, and Simón Bolívar University

Figure 1: Evolution of Venezuelan Migration in Colombia (2013-2019)



Note: The figure displays the quarterly evolution of migrants in Colombia represented both as a percentage of the Colombian population and of the total employment. The solid vertical line divides the periods before and after the reopening of the Venezuela-Colombia border.

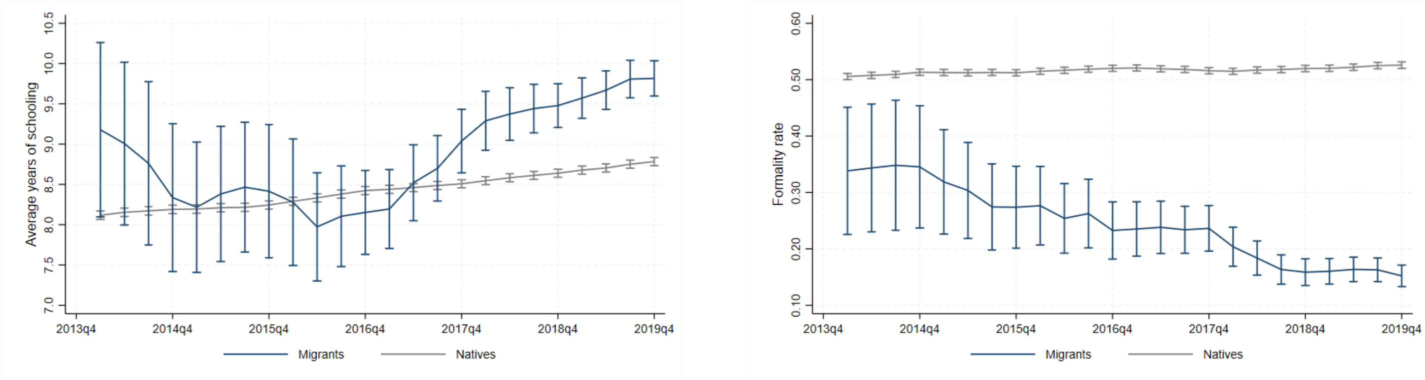
Panel A of Figure 2 shows the evolution of the educational level of migrants that arrived in Colombia, measured in average years of schooling. Between 2013 and 2017, the educational level of migrants was at similar levels to that of natives: between 8 and 8.5 years of education. Afterwards, migrants that arrived had higher qualifications than natives, averaging 9.9 years of education by the end of 2019, in contrast to 8.8 for natives.

Additionally, the migrant population has shown very low levels of labor formalization, defined as the affiliation with the contributive health system[5]. While the labor formality of natives increased between 2013 and 2019, from 50% in 2013 to 52% by the end of 2019, that of migrants decreased, from 34% in 2013 to 17% in 2019 (Figure 2, Panel B).

[5] There are several approaches to measure labor informality in Colombia. The official DANE methodology classifies informal workers based on the size of their employing company, specifically targeting those in firms with fewer than five employees. However, this metric is not often used by the literature studying labor markets in Colombia because it (i) overlooks formal workers in small firms or those self-employed, and (ii) may misidentify workers in larger firms as formal when they might be informal. Consequently, this paper adopts a most used and accurate criterion, defining formal workers as those contributing to social security, particularly to the health system.

Figure 2: Evolution of Educational Level and Formality Rate: Migrants vs Natives

A. Average Years of Education **B. Formality rate**



Note: Left and right panels displays the share of migrants and natives working in the formal labor market, and their average years of schooling, respectively, using 4-quarter rolling averages from the GEIH-DANE survey spanning 2013 to 2019 with 95% confidence intervals.

Furthermore, I examined the distribution of migrants across the main economic sectors before and after the reopening of the border (Table 1). Between 2013Q1 and 2016Q2, migrant workers represented less than 0.5% of total workers in all sectors. Although there was a general increase in the number of migrants afterward, considerable heterogeneity was observed across sectors. Hotels and Restaurants, Construction and Retail saw the highest rise, where the share of migrants passed from 0.5%, 0.6% and 0.3% prior to the reopening of the border to 6.9%, 4.3% and 2.9% afterwards, respectively. The Retail sector accounted for the highest absolute number of migrants in the latter period, totaling an average of 120,755 (from 12,565 in previous years). Other sectors, in contrast, exhibit smaller growth, including Mining, Electricity, Gas and Water, and Agriculture.

Table 1: Distribution of Migrants by Economic Sectors

	Number of migrants		Share of migrants	
	2013Q1-2016Q2	2016Q3-2019Q4	2013Q1-2016Q2	2016Q3-2019Q4
Agriculture	9,284	53,841	0.003	0.014
Mining	1,193	1,842	0.004	0.007
Manufacturing	9,313	71,084	0.004	0.026
Electricity, Gas and Water	245	2,168	0.002	0.012
Construction	8,714	64,978	0.006	0.043
Retail	12,565	120,755	0.003	0.029
Hotels and Restaurants	6,825	105,771	0.005	0.069
Transportation and Storage	4,654	26,633	0.003	0.018
Financial and Real Estate	1,870	8,974	0.003	0.016
Technical and Professional	3,069	28,620	0.002	0.015
Services	9,974	82,795	0.002	0.020

Note: This table shows the distribution of migrants across the main economic sectors before and after the border reopening. Data are sourced from the GEIH-DANE.

III. DATASET AND EMPIRICAL STRATEGY

In order to estimate the impact of Venezuelan migration on Colombian labor productivity, I built a quarterly panel dataset at the industry level combining several sources of data. Using National Accounts Statistics from Colombia's National Statistical Office (DANE), I decomposed Colombia's quarterly GDP (y_t) from 2013 to 2019 into 50 industries, detailed in Table A.1 of the Online Appendix. Then, I construct labor variables for each industry and quarter using data from the GEIH. This survey, conducted by DANE, serves as the primary resource for socio-demographic data, as well as labor, income, and poverty indicators in the country. This dataset allows me to calculate total employment (l_{it}) and average hours worked (h_{it}) for each industry i and quarter t, to calculate the output per hour worked (pl_{it}), the main measure of labor productivity.

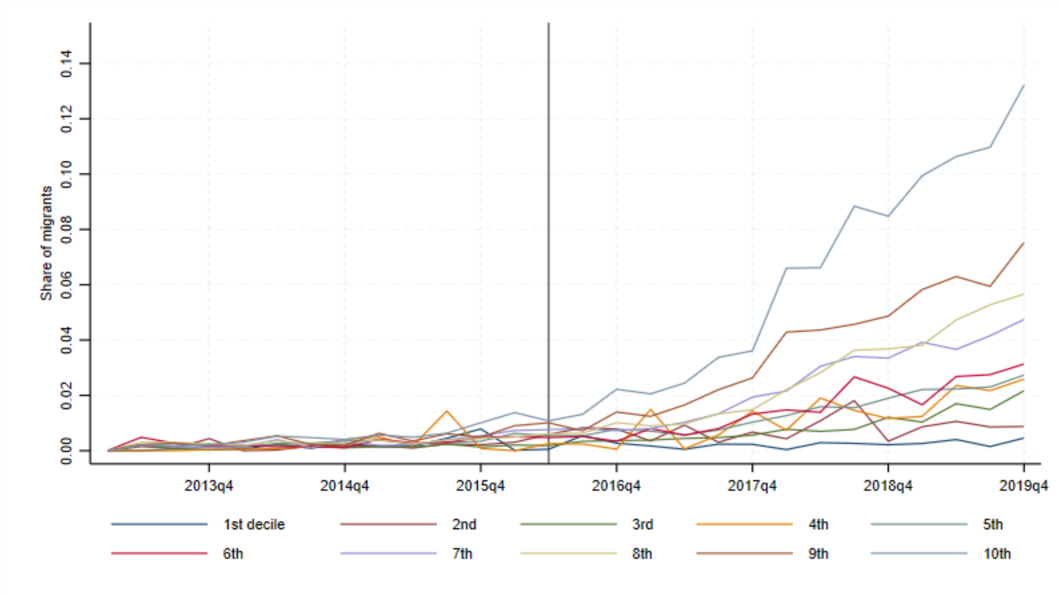
After 2013, the GEIH included additional questions that enabled the identification of individuals' nationality and the place where they lived one year and five years prior to the interview. Based on this information, I built the "Venezuelan migration" variable (m_{it}), defined as the proportion of workers in an industry i in quarter t who lived in Venezuela 5 years earlier[6]. Additionally, the GEIH allows us to know the educational level of workers and whether they work in the informal or formal sector.

The main methodological challenge in estimating the effect of migration on productivity derives from the fact that migration is not randomly distributed among industries, generating evident endogeneity problems. This endogeneity issue stems from at least two potential scenarios: first, industries with positive productivity trends might attract more migrant workers; or second, migrant workers may gravitate towards less-productive industries where obtaining informal employment is easier, especially in the absence of a work permit.

To overcome this problem, I use a continuous or "dose-response" difference-in-difference methodology, leveraging the exogenous timing of the border reopening in the third quarter of 2016. As shown in Figure 3, the migration share before the border reopening was very low in all industries. After the shock, industries experienced different "doses" of migration. While some maintained a low migration presence, others saw surges of migrants, eventually constituting more than 10% of the workforce.

[6] I chose this migration measure because (i) taking only those who were born in Venezuela would hide migrants coming from Venezuela but with a different nationality (for example, Colombian returnees) and (ii) the variable that defines migrants as "those who lived in Venezuela 12 months ago" does not consider as migrants those who have been in Colombia for more than a year: thus, if a migrant arrived in the country more than a year ago but has just entered the labor market, they will no longer be considered a migrant, and this may bias the results.

Figure 3: Evolution of Migration Share by Deciles of Industries



Note: The figure illustrates the evolution of migration share across deciles of the 50 industries examined. Decilization was conducted using the average migration share after the second quarter of 2016.

My empirical approach capitalizes on this variation in migration intensities to examine shifts in productivity. Specifically, I defined the following equation:

$$pl_{it} = \theta_t + \eta_i + \beta(m_{it} \times post_t) + \varepsilon_{it} \tag{1}$$

The variable $post_t$ is a dummy that equals 1 for periods after the second quarter of 2016 when the border was reopened. Labor productivity (pl_{it}) is defined in logarithm form. β is the coefficient of interest, as it measures the differential change in output per hour worked after the reopening of the border attributable to a one percentage point increase in the share of migrant workers. The equations include industry fixed effects, η_i, to control for unobservable time-invariant factors at the industry level that affect productivity, and quarter fixed effects, θ_t, to account for common shocks in specific periods that affect all industries. Standard errors in these and all following specifications are clustered at the industry level to account for potential serial correlation across industries over time.

I performed two additional exercises to assess the robustness of my main results. First, I used "output per worker" (yl) as an alternative measure of labor productivity. Considering both productivity measures (yl and pl) allows me to identify if efficiency changes arise from intensive or extensive margins. Specifically, it is possible to identify if migrant workers increase or reduce output working similar time frames or if these changes derive from working more or fewer hours than natives. However, "output per hour worked" is my preferred measure of productivity, as it accounts for variations in work hours across industries and seasons[7].

[7] This measure of labor productivity has been extensively used in the literature. See, for example, O'Mahony and Timmer (2009) Jorgenson *et al.* (2008), Inklaar *et al.* (2008) and Vatsa and Pino (2023).

Second, I re-estimated equation 1 including interacted year $\times$ industry fixed effects. The objective of this exercise is to check that the effects on productivity are not driven by time-variant shocks that differentially affect certain industries.

As discussed by Callaway *et al.* (2021), the continuous difference-in-difference approach relies on stronger assumptions compared to the binary-treatment setting. Similar to the binary case, the identification of treatment effects is valid under the *standard parallel trends assumption*. This assumption implies that the average change in outcome for units experiencing a certain dose d would have been similar to untreated units had they not been exposed to any level of the dose. However, in the continuous setting, it is necessary to assume that the average causal response does not vary across dose levels, which is called the *strong parallel trends assumption*. Specifically, this means assuming that the average change in outcome for high-dose units would have been similar to the response of low-dose units if they had been exposed to low-dose treatments.

To check if the standard parallel trends assumption holds, I exploited the information from the pre-treatment periods to estimate a dynamic difference-in-difference equation defined as follows.

$$pl_{it} = \theta_t + \eta_i + \sum_{t \in T-1} \beta_t (m_{it} \times quarter_t) + \varepsilon_{it} \tag{2}$$

where $quarter_t$ is set to 1 for all observations within quarter t. The first quarter of 2016 was omitted to benchmark the coefficients against the period preceding the shock. If β_t coefficients for pre-shock periods are not significantly different from zero, then there is no evidence of productivity pre-trends prior to the border reopening, making the standard parallel trends assumption more credible.

Testing the validity of the strong parallel trends assumption is more challenging, as there are no suitable counterfactuals for industries exposed to higher levels of migration as if they were exposed to lower levels of migration. Nevertheless, if the dose is balanced across covariates, the assumption is more likely to hold. Following the approach of Cook *et al.* (2023), Figure A.2 of the Online Appendix displays the correlation of pre-treatment covariates and the average post-treatment migration share. The results show that most of the variables are balanced across intensities of the migration share except in the formality rate and size of the workforce, potentially due to the fact that larger and more informal industries tend to present fewer barriers for migrants to access. Interestingly, as shown in Figure A.3 of the Online Appendix, the relation between the dose and the unbalanced covariates was stable across all pre-treatment periods.

Productivity changes resulting from migration can be driven by different types of adjustments in labor markets and economic activity. One potential scenario is that migration leads to the substitution of local workers with migrant workers without significant changes in overall output. Alternatively, the positive labor supply shock derived from migration could have allowed firms to scale up production and recruit additional workers rather than replace the existing workforce. It is also plausible that a combination of both scenarios played out: changes in both output and composition of the workforce. To better understand the nature of productivity changes, I re-estimated equation 1 using the logarithm of output, y_it, employment, l_it, and hours worked, h_it, as dependent variables.

In this specifications, β coefficients capture the differential change in output, employment and hours worked, respectively, in response to a one-percentage-point increase in the migration share.

Furthermore, the dataset enables the examination of heterogeneous effects influencing the productivity gains of migration. Specifically, I assess how migration responses might differ based on the migrants' educational levels and the obstacles they face in accessing the formal labor market. To achieve this, I modified equation 1 by introducing as interaction terms the average years of schooling for migrants, k_{it}, and migrants' formality rate, f_{it}, in each industry i during quarter t. These terms are included separately in equations 3 and 4.

$$pl_{it} = \theta_t + \eta_i + \phi_1(m_{it} \times post_t) + \delta_1(k_{it} \times post_t) + \gamma_1(k_{it} \times m_{it}) + \beta_1(k_{it} \times m_{it} \times post_t) + \varepsilon_{it} \quad (3)$$

$$pl_{it} = \theta_t + \eta_i + \phi_2(m_{it} \times post_t) + \delta_2(f_{it} \times post_t) + \gamma_2(f_{it} \times m_{it}) + \beta_2(f_{it} \times m_{it} \times post_t) + \varepsilon_{it} \quad (4)$$

In the latter specifications, β_1 represents the impact of migration on productivity after the border reopening in response to a one-year increase in migrants' schooling. In a similar vein, β_2 captures the effect of migration on productivity as the labor formality among migrants rises by one percentage point.

IV. RESULTS

Table 2 displays the β coefficient estimated from equation 1. Column 1 results indicate that a one-percentage-point increase in the proportion of Venezuelan migrants caused a 7.6% output per hour worked.

Table 2: Effect of Migration on Productivity

	Output per hour worked (ln)
Share of migrants × post	0.0761***
	(0.0210)
N	1395
Adjusted R2	0.937

Note: This table displays the estimation of equation 1 for the logarithm of output per worker and output per hour worked, including period and industry fixed effects. Clustered robust standard errors at the industry level are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.2 from the Online Appendix shows that these results are robust to changes in the definition of labor productivity and alternative fixed effects specifications. Specifically, the first exercise uses "output per worker" as the dependent variable. The effect (-6.4%) is significant and slightly lower than the one observed using "output per hour worked" (-7.6%). This differential suggests that migrant workers might be generating more output for each hour worked but are probably working fewer hours overall. The second column shows the results, including interacted year × industry fixed effects. Although the magnitude of the coefficient under this specification is slightly lower (-5.1%), it remains significant at the 95% confidence level.

The validity of this estimate relies on the assumption of no pre-existing trends between industries with high migrant inflows and those with fewer. To verify this assumption, I estimated the dynamic difference-in-difference model outlined in equation 2. As shown in Figure A.1 of the Online Appendix, point estimates from quarters prior to the border reopening are not statistically different from zero, both at the 90% and 95% confidence levels, indicating no evidence of pre-trends.

To decompose the positive effect on productivity, I estimated the main specification using GDP, employment and average hours worked as the dependent variables. The results, presented in 3, suggest that a one p.p. increase in the share of migrants has a negligible effect on output. By contrast, a similar increase in migration reduces employment by 5.9% and average hours worked by 1.2%. These results imply two conclusions. First, the positive effect on productivity emerges from reductions in employment and hours worked rather than a surge in economic activity. Second, there seems to be a substitution effect where some native workers are replaced by a smaller number of migrants.

Table 3: Decomposition of the Effect on Productivity: Output, Employment and Hours Worked

	(1)	(2)	(3)
	Output (ln)	Number of workers (ln)	Average hours worked (ln)
Share of migrants × post	0.00481	-0.0593**	-0.0120**
	(0.00759)	(0.0223)	(0.00511)
N	1395	1395	1395
Adjusted R2	0.996	0.972	0.655

Note: This table displays the estimation of Equations 1 with the logarithm of output, employment and average hours worked as dependent variables. All regressions include period and industry fixed effects. Clustered robust standard errors at the industry level are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Lastly, I explore two heterogeneous effects behind the observed productivity changes: the educational level of migrants and their access to the formal labor market. To test these heterogeneous effects, I estimate equations 3 and 4, which incorporate the average years of schooling and the formality rate of migrants, respectively, as additional interaction terms in the model. The results are summarized in Table 4. The effect of migration on productivity—measured by output per hour worked—is 0.07 percentage points higher for every additional year of schooling of migrants (Panel

A). The marginal effect for every level of education of migrants, from 0 to 20 years of schooling, is calculated in Figure in Panel B of Figure 4. When migrants have between 0 and 8 years of schooling, on average, an increase in migration is estimated to have a null impact on labor productivity. On the other hand, when migrants have, on average, more than 10 years of schooling, an increase in migration boosts productivity substantially.

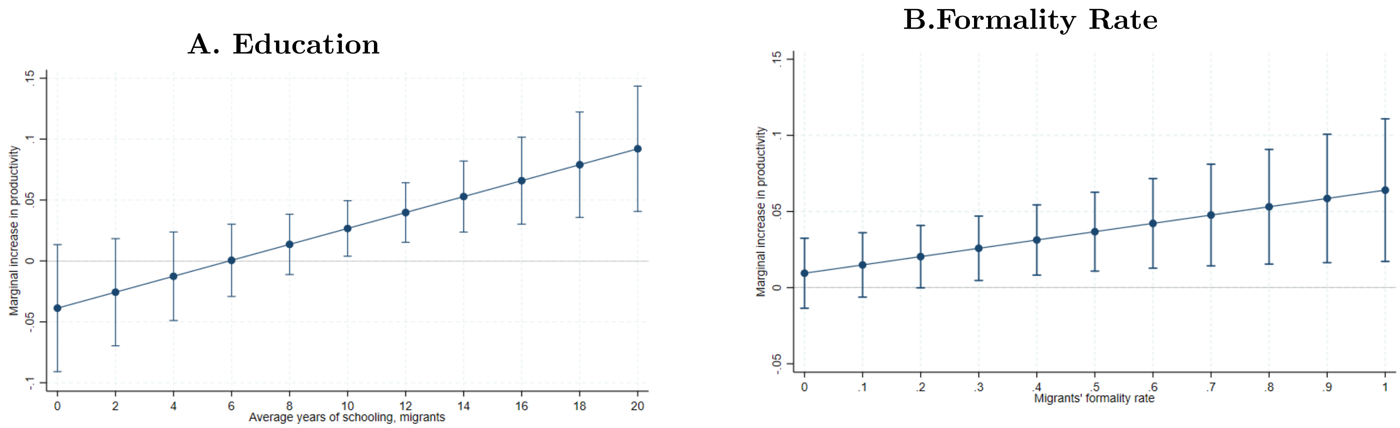
Panel B of Table 4 exhibit a similar trend by migrants' formality rate. The effect on productivity is 0.05 higher for every percentage point increase in labor formalization. This marginal effect is depicted in Panel B of Figure 4 across various formality ranges. When migrants' formality is below 20%, the effect on productivity is not significant. Elevated formality rates correspond to notable productivity gains: from a 2.5% boost at 30% formalization to exceeding 6% with full labor formalization.

Table 4: Effect of Migration on Productivity by Educational Level and Formality Rate

	Output per hour worked (ln)
A. Educational level	
Share of migrants × post × years of education	0.00654***
	(0.00237)
N	1015
R2	0.975
B. Formality rate	
Share of migrants × post × formality rate	0.0546**
	(2.04)
N	1016
R2	0.974

Note: This table displays the estimation of equations 3 and 4. Clustered robust standard errors at the industry level are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Figure 4: Marginal Effect of Migrants' Education and Formality Rate on Productivity



Note: Left panel displays the marginal effect of migrants' educational level on productivity, measured by average years of schooling, from Panel A of Table 4. Right panel shows the marginal effect of migrants' formality rate on productivity from Panel B of Table 4. Confidence intervals constructed at 95% confidence level.

V. CONCLUDING REMARKS

The literature has extensively revised the implications of migration on productivity, but forced migration episodes are rarely the case of study. Furthermore, analyzed host economies are typically high-income ones, with small informal labor markets and strong labor institutions. The Venezuelan migration influx to Colombia during the past decade stands as a compelling setting to study the productivity impacts of forced migration between developing countries. Despite a higher educational background among Venezuelan migrants compared to native Colombians, a significant proportion of these migrants ended up in the informal labor market, potentially leading to mixed impacts on productivity.

This paper assesses the impact of Venezuelan mass migration to Colombia on labor productivity by exploiting two sources of variation: (i) the reopening of the Colombia-Venezuela border in 2016 amidst Venezuela's intensifying economic and social turmoil and (ii) the dispersion of migrants across 50 industries after the shock.

Results show that Venezuelan migration had a positive effect on Colombian labor productivity. Interestingly, this rise stems from employment adjustments rather than from a boost in production, suggesting a displacement of some native workforce by migrants. This result aligns with the existing literature, which has revealed a negative impact of migration on native labor outcomes, especially for those less skilled. Furthermore, two heterogeneous effects were found, suggesting that the positive effects were driven by the higher skill level of migrants and somewhat counteracted by the barriers to formality faced by them.

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A. Online Figures and Tables

Table A.1: Disaggregation of Industries Included in the Panel Dataset

Industry Name
Agriculture and livestock
Forestry and timber extraction
Fishing and aquaculture
Mining of brown coal and lignite
Crude oil and natural gas extraction
Extraction of metalliferous minerals
Other mining and quarrying
Support activities for other mining and quarrying activities
Manufacture of food products
Manufacture of beverages and tobacco products
Preparation, spinning, weaving and finishing of textile products
Leather tanning and retanning
Wood processing and manufacture of wood and cork products
Manufacture of paper, paperboard, paper and paper products and paperboard products
Printing activities
Coking, manufacture of petroleum refining products and fuel blending activities
Manufacture of basic chemicals, fertilizers and inorganic nitrogen compounds, plastics and synthetic rubber
Manufacture of rubber and plastic products
Manufacture of other non-metallic mineral products
Manufacture of basic metallurgical products
Manufacture of electrical components and equipment
Manufacture of machinery and equipment
Manufacture of motor vehicles, trailers and semi-trailers
Manufacture of furniture, mattresses and bed bases
Other manufacturing industries
Generation, transmission, distribution and commercialization of electric energy and gas
Water collection, treatment and distribution
Evacuation and treatment of wastewater
Recovery of materials (recycling)
Construction of residential and non-residential buildings
Construction of roads and railroads, public utility projects and other civil engineering works
Specialized activities for the construction of buildings and civil engineering works
Wholesale and retail trade
Maintenance and repair of automotive vehicles and motorcycles
Inland transportation and pipeline transportation
Water transportation
Air transportation
Warehousing and ancillary transport activities
Mail and courier service activities
Lodging and food services
Information and communications
Financial and insurance activities
Real estate activities
Professional, scientific and technical activities
Administrative and support service activities
Public administration and defense
Education activities
Human health care and social service activities
Arts, entertainment and recreation and other service activities
Activities of individual households as employers

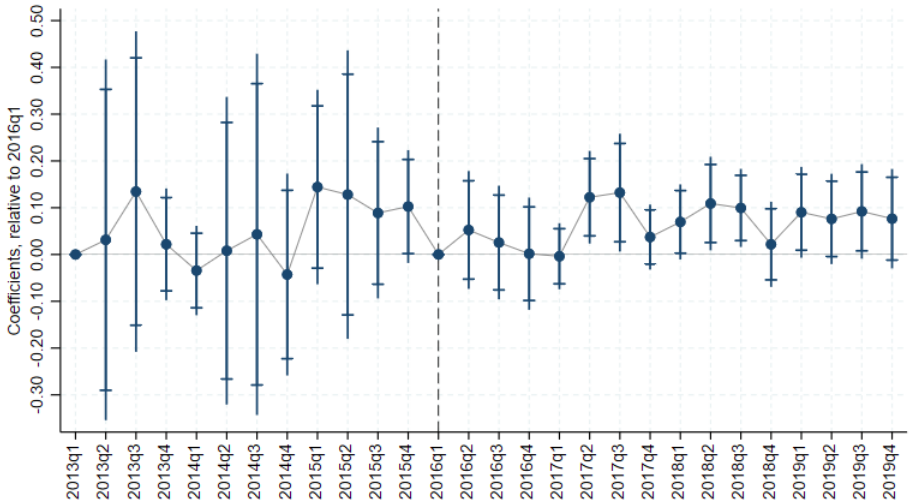
Note: This disaggregation reflects the greater level of detail that can be obtained by pooling the GDP database from the national accounts and the DANE's GEIH, based on International Standard Industrial Classification of All Economic Activities, Rev. 4 (ISIC-4). All covariates are computed from the GEIH survey, except for exports and imports, which are retrieved from DANE's official trade records

Table A.2: Robustness Exercises

	(1)	(2)
	Alternative meassure of productivity	Intercated year × industry fixed effects
Share of migrants × post	0.0641***	0.0510**
	(0.0180)	(0.0191)
N	1395	1395
Adjusted R2	0.936	0.949

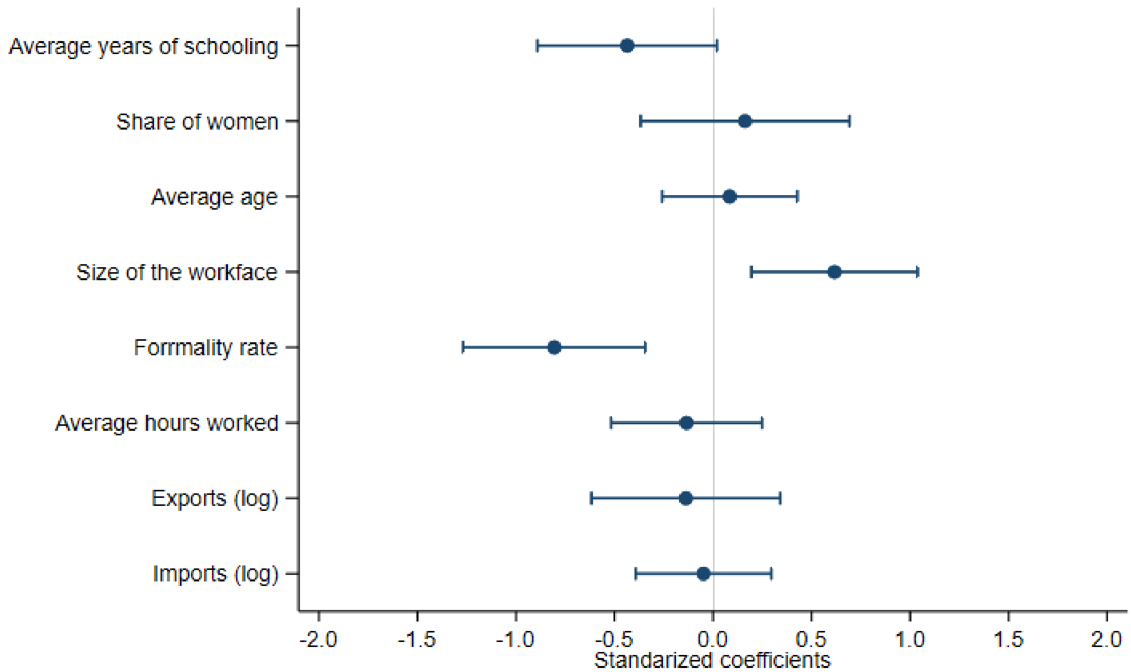
Note: This table displays the results of some variations in estimating equation 1. The first model uses "output per worker" as the dependent variable, and the second model includes year × industry fixed effects instead of separate quarter and industry fixed effects. Clustered robust standard errors at the industry level are in parentheses.

Figure A.1: Effect of Migration on Productivity: Dynamic Difference-in-Difference Model



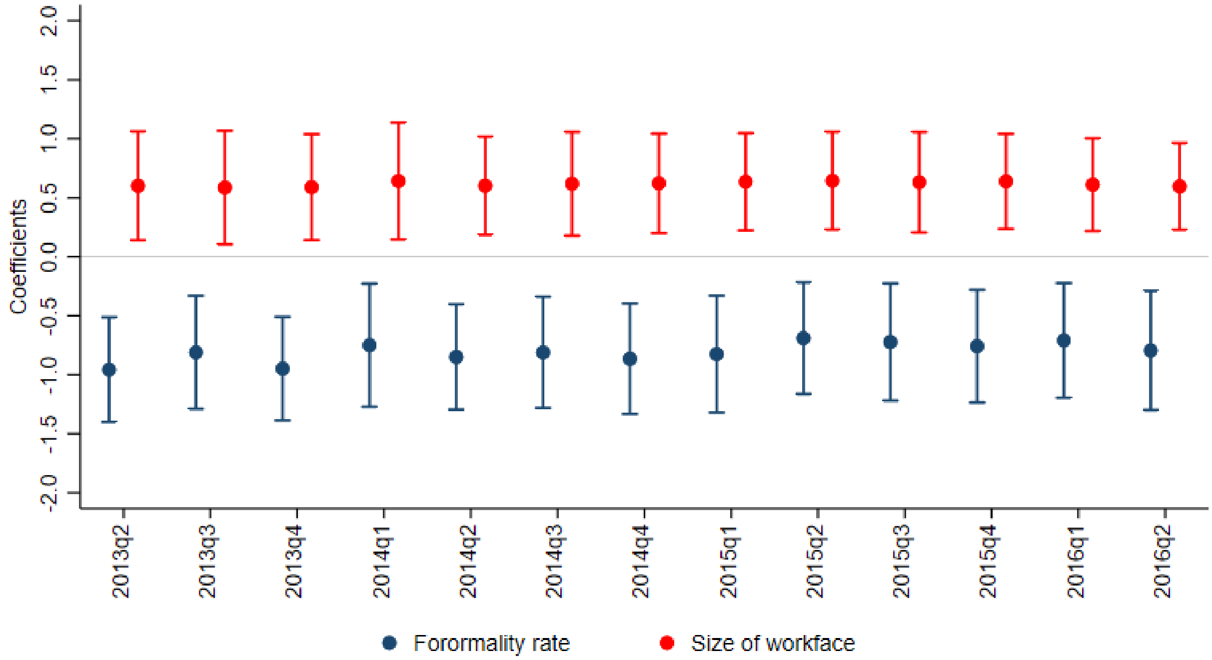
Note: The figure shows quarterly point estimates, along with the 90% and 95% confidence intervals of the dynamic difference-in-difference model defined in equation 2. Standard errors are clustered at the industry level.

Figure A.2: Correlation between Post-Shock Migration Share and Pre-shock Covariates



Note: This figure displays the standardized coefficient from separate regressions of the average migration share between 2016Q3-2019Q4 and each covariate before the border reopening. All regressions include quarter-fixed effects. Error bars represent 95% confidence intervals computed using cluster standard errors at the industry level.

Figure A.3: Correlation between Post-Shock Migration Share and Pre-Shock Covariates



Note: This figure displays the standardized quarter-point estimates from individual regressions for the average migration share between 2016Q3 and 2019Q4, in relation to the formality rate and workforce size separately. Error bars indicate 95% confidence intervals, computed using cluster standard errors at the industry level.