Three essays on migration and education

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A la memoria de mi abuelo y gran amigo, José Aristóbulo López Nava

Foreword

This document is the result of a research project carried out at the Department of Economics of the Universidad del Rosario (UR).

This document is submitted as a doctoral thesis at UR. In keeping with the policies of UR, the author has been entirely free to conduct and present his research in the manner of his choosing as an expression of his own ideas.

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A mi familia, por creer en mí y apoyarme. Especialmente, agradezco a mi mamá que siempre le apostó a la educación como el mejor camino para crecer. A mi abuela Amparo y a mi hermano Jose Luis, por ser el lugar donde siempre puedo llegar. A Juan David Guerrero, mi mejor amigo, que ha confiado en mí, más que yo misma.

A mi abuelito, que siempre estuvo y estará aquí.

Contents

Introduction

This Ph.D. thesis investigates two central topics, namely, (i) the impact of Venezuelan migration on the Colombian labor market and (ii) the relationship between the expansion of illicit crops and educational outcomes in rural areas. Chapter 1 analyzes how informal labor market outcomes vary across productive sectors in response to the labor supply shock induced by Venezuelan migration between 2015 and 2019. I find that migration exerts downward pressure on informal wages and employment among local workers, with the strongest effects concentrated in the Construction, Real Estate, and Services sectors. These results point to a substitution effect, particularly affecting low-skilled and self-employed informal workers. Furthermore, I show that micro and small firms, typically low-productive and more likely to operate informally, tend to absorb migrant labor by offering informal employment at lower wages. These firms appear to take advantage of migrants' greater willingness to work longer hours for lower pay, especially in labor-intensive segments of Construction and Real Estate.

Chapter 2, co-authored with Darwin Cortés, Mariana Blanco, and Gabriela Triviño, builds on the insights from Chapter 1 by identifying potential labor market discrimination towards Venezuelan migrants in Colombia. We design and implement a laboratory experiment using an Incentivized Resume Rating (IRR) framework to examine two central questions: (i) whether recruiters perceive Venezuelan applicants as less likely to be recommended for a job compared to Colombian applicants, and (ii) whether recruiters expect bias from their peers, even if they themselves do not discriminate. The results reveal evidence of positive discrimination in favor of Venezuelan candidates, both when recruiters make individual choices and when they predict others' preferences. This pattern appears to be partially driven by the skill level required for the job vacancies. Importantly, we find no evidence of taste-based discrimination: recruiters tend to correctly identify and recommend the better-performing candidate, and their attitudes toward potential bias or social risk do not shape their hiring decisions.

Last, Chapter 3, co-authored with Darwin Cortés and Omar Garzón, evaluates the causal impact of coca cultivation on educational outcomes in rural Colombia, leveraging the 2014 announcement of the National Illicit Crop Substitution Program (PNIS) as an exogenous source of variation. Combining georeferenced panel data on rural schools with satellite imagery on coca crops from 2013 to 2019, we implement a difference-in-differences estimator that is robust to both continuous and dynamic treatments. Our findings show that increases in coca cultivation within a 1 km radius of a school lead to immediate declines in school enrollment and subsequent rises in school dropout rates. These effects are strongest at the elementary level, which is consistent with the fact that rural education in Colombia is predominantly concentrated at that level. Although failure rates do not exhibit consistent patterns overall, significant increases are observed within 5 km buffers. Furthermore, we find that girls are disproportionately affected in terms of school enrollment. Overall, educational outcomes respond not only to the presence of coca crops near schools but also to the intensity of coca expansion.

Chapter 1

Venezuelan migration, wages and employment of informal workers in Colombia at the sector level

Nazly López-Peña

1.1. Introduction

Since 2013, Latin America has experienced one of the largest migration waves in its recent history. The collapse of Venezuela's political and economic institutions led to the displacement of approximately seven million people by 2024 (ACNUR, 2022; Bahar et al., 2021; Bonilla-Mejía et al., 2020; IOM, 2022; Rozo and Vargas, 2021), the majority of whom have sought refuge in neighboring countries. Due to its geographic proximity and cultural ties, Colombia has received an estimated 2.5 million Venezuelan migrants during this period, with most settling in border departments and major urban centers in search of better living conditions (Migración Colombia, 2021).

As a result, the Colombian labor market has absorbed a substantial labor supply shock since the onset of the Venezuelan crisis, which was intensified in 2015 after the Venezuelan government announced the closure of the Simón Bolívar Bridge, the principal border crossing point between the two countries.

This massive labor supply shock presents significant challenges for the host country, particularly from two key perspectives. First, the majority of Venezuelan migrants arrive under conditions of socioeconomic vulnerability, driven by the economic and political crisis in their country of origin. Many migrants lack the resources, documentation, or credentials required to access formal employment. Others face a trade-off between contributing to the social insurance system and meeting their basic needs. Taken together, these constraints substantially increase the likelihood that migrants enter informal labor segments, typically characterized by lower wages than those of native workers (G. Borjas, 2003; Card, 2001; Gindling, 2009; Sinning, 2014; Theoharides, 2018; Viseth, 2020).

Second, the Colombian labor market itself is structurally fragile, characterized by high informality (which yields approximately 50% of the employment), and a predominance of low-productive firm structures (in which micro & small firms account for 92% of all firms (DANE, 2023)). Together, these conditions create a fertile ground for downward wage pressures and employment displacement for locals (G. J. Borjas, 1998; G. J. Borjas and Chiswick, 2019; Nowotny, 2012; Sinning, 2014), given that around 90% of worker migrants are linked in those segments, where there is no binding minimum wage. Moreover, the scenario potentially increases job competition among both informal local workers and migrants, particularly those in low-skilled occupations (Bahar et al., 2021; Bonilla-Mejía et al., 2020; Caruso et al., 2019; Delgado-Prieto, 2024; Peñaloza-Pacheco, 2019).

Given the scale and characteristics of this phenomenon, Venezuelan migration has attracted growing attention in the recent empirical literature. Sanramaria (2022) finds that, despite Colombia's open-door immigration policy, the labor market effects of migration have been limited, reporting only modest declines in informal wages and no significant impacts on broader employment outcomes. In this regard, Bahar et al., 2021 evaluates the *Permiso Temporal de Permanencia* (PTP) program and concludes that it had no statistically significant effects on labor formality among migrants.

In contrast, Caruso (2019) documents more substantial effects: an overall wage reduction of 8 percentage points, a sharper decline of 10 percentage points in informal sector wages, and a 2 percentage point decrease in employment in urban areas. Delgado-Prieto (2024) finds a decline in average wages ranging between 1.6% and 1.7%, with a more substantial impact of 1.9% for informal wages. Additionally, the study documents a 2.2% decrease in formal employment, while no significant effects are observed for informal employment.

Additionally, Bonilla-Mejía et al. (2020) report a 1.15 percentage point increase in migrant unemployment, along with a reduction in the probability of participation and employment among local workers by 1.65 and 2.21 percentage points, respectively, particularly among the self-employed. Similarly, Peñaloza-Pacheco (2019) finds that Venezuelan migration reduces wages by 0.4% and lowers employment rates for low-skilled workers by 0.1 percentage points.

This study examines the impact of Venezuelan migration on labor market outcomes in Colombia, with a particular emphasis on the informal segment across productive sectors. This focus is motivated by the high concentration of migrants in informal employment and the direct competition they face from low-skilled local workers. As documented in the literature, informal labor segments tend to exhibit the most pronounced responses to large labor supply shocks.

I further argue that specific productive sectors may drive aggregate effects for two main reasons. First, migrants tend to concentrate in sectors with lower entry barriers, where informal employment is prevalent. Second, labor market outcomes in certain sectors may exhibit greater elasticity to supply shocks, particularly where firms seek to minimize costs and can more readily substitute native workers with migrant labor (G. Borjas, 2014; Delgado-Prieto, 2024).

I focus on six large sectors of the Colombian economy [1], include Manufacturing, Construction, Commerce (which encompasses Hotels and Restaurants), Transport, Storage, and Communications (hereafter, Transport), Real Estate, and Private, Communal, and Personal Services (hereafter, Services), for 24 urban areas representative of 98% of the population.

To identify the causal effects of Venezuelan migration on informal labor outcomes, I implement an identification strategy that addresses potential endogeneity and reverse causality given the self-selection of migrants across time and geographic areas. Specifically, I employ an Instrumental Variables (IV) approach based on a shift-share design, which is widely used in the migration literature (G. Borjas, 2003; Card, 2001; Caruso et al., 2019; Del Carpio and Wagner, 2015; Delgado-Prieto, 2024; Dustmann et al., 2016; Jaeger et al., 2018).

For the instrument, I constructed a triple interaction that captures exogenous variation in migrant distribution across Colombian departments. It combines: (i) a historical settlement network of Venezuelans already established in various regions of the host country, which tends to attract new arrivals through peer effects; (ii) the geographic distance between the centroids of Venezuelan origin states and the centroids of Colombian departments, which proxies the cost of migration; and (iii) a time-varying measure of the aggregate migrant inflow since the onset of the crisis. This shift-share structure enables a plausible exogenous allocation of current

[1] According to the CIIU v4 classification by DANE. The agricultural sector is excluded because the sample focuses on urban areas. Similarly, the mining and public services sectors are omitted due to the small sample size in these categories.

migration flows, driven by pre-existing networks and migration frictions rather than local labor market conditions.

Overall, I find that a one-percentage-point increase in the Venezuelan labor supply shock leads to a 0.04% reduction in informal wages and a 0.01% decline in local informal employment. These modest aggregate effects, however, conceal substantial heterogeneity across sectors. The Construction and Real Estate sectors emerge as the most affected, exhibiting wage reductions of 0.11% and 0.07%, respectively.

In terms of employment, informal job losses are particularly pronounced in the Construction and Services sectors, with estimated declines of approximately 0.06% and 0.03%. I do not obtain statistically significant effects on formal labor outcomes at the aggregate level, likely due to the binding minimum wage. Nonetheless, formal wages in the Real Estate and Services sectors still experience modest declines, suggesting that even regulated segments of the labor market are not entirely insulated from the shock.

Interestingly, in the Real Estate sector, the most capital-intensive among all sectors, the negative effects are primarily concentrated in labor-intensive occupations. I find that the wage response is primarily driven by blue-collar roles, with informal wages declining by approximately 0.10% for each one-percentage-point increase in the migrant labor supply.

Additionally, self-employed workers emerge as the most affected group across nearly all sectors, and micro and small firms, typically characterized by low productivity structures (G. Borjas, 2014), are more likely to employ migrant labor informally. In these firms, wage reductions are even more pronounced; among small firms, informal wages drop by up to 0.28%. In terms of employment, informal local workers in small firms within the Construction and Services sectors experienced declines of 0.14

The heterogeneous effects reveal, first and foremost, that informal local workers with less than a high school education experience the most substantial declines in both wages and employment across nearly all sectors. On the other hand, in the Construction sector, wage reductions are widespread across all demographic groups. Still, they are especially pronounced among men, younger workers, and those with lower levels of education. In the Real Estate sector, wage losses are more concentrated among middle-aged workers of both genders. In terms of employment, the effects are more limited in scope; male workers experience declines primarily in the Services sector but show slight increases in Manufacturing.

Overall, my estimates remain robust when excluding border cities between Colombia and Venezuela. Additionally, due to the nature of my instrument, it is crucial to ensure that the observed effects are not driven by correlations with the 2005 census but rather by the networks of peers themselves. Overall, I find that my estimates are consistent and robust when accounting for previous migrant settlements recorded in the 1993 census.

Lastly, some pre-existing characteristics at the department level, such as access to social goods and services, economic dynamics, public expenditure, and other factors, may potentially attract migrants. However, the analysis indicates that migration is not sensitive to department-level pre-trends, and the estimates remain robust across these considerations.

Overall, this study contributes to the growing literature on the labor market effects of Venezuelan migration in developing countries (Bahar et al., 2021; Bonilla-Mejía et al., 2020; Caruso et al., 2019; Delgado-Prieto, 2024; Lebow, 2022; Peñaloza-Pacheco, 2019; Rozo and Vargas, 2021; Santamaria, 2022). Its main contribution lies in the sectoral disaggregation of labor market outcomes, which enables the identification of heterogeneous effects across productive sectors, a feature that aggregate analyses tend to overlook. While previous studies have largely focused on average impacts at the national or urban level, this paper reveals that the magnitude and direction of migration effects vary substantially depending on sector-specific dynamics. In particular, differences in labor/capital intensity, skills, and productive structures of firms shape the degree to which local workers are substitutable by migrant labor.

In addition to the introduction, this work comprises seven more sections. Section 2 presents a general overview of the origins of Venezuelan migration and the arrival of migrants in Colombia. Section 3 describes the data and some descriptive statistics. Section 4 shows the identification strategy and the construction of the Instrumental Variable. Section 5 reports the results, Section 6 details the heterogeneous effects, and Section 7 reports the robustness checks. Finally, Section 8 concludes with a discussion.

1.2. Venezuelan immigration and the Colombian labor market

Between 2013 and 2020, Venezuela experienced a hyperinflationary phenomenon, with cumulative inflation exceeding 130,000%, and the cost of the family shopping basket increasing by 700% (BCV, 2021; Mazuera-Arias et al., 2020) during that period. For 2017, reports indicated that six out of ten Venezuelans had involuntarily lost an average of 22 pounds, and nine out of ten could not afford a daily diet (ENCOVI, 2017). That same year, the homicide rate reached 89 per 100,000 inhabitants, added to an increase in reports of human rights violations attributed to the regime (EASO, 2020; Statista, 2023; World Bank, 2020). By 2018, 91% of the population was living below the poverty line, and approximately 20,000 infant deaths were attributed to the ongoing crisis in the country (ENCOVI, 2018). These conditions triggered one of the largest humanitarian crises in recent Latin American history, with over seven million Venezuelans displaced worldwide by 2023 (ACNUR, 2022; Bonilla-Mejía et al., 2020; Bull and Rosales, 2020).

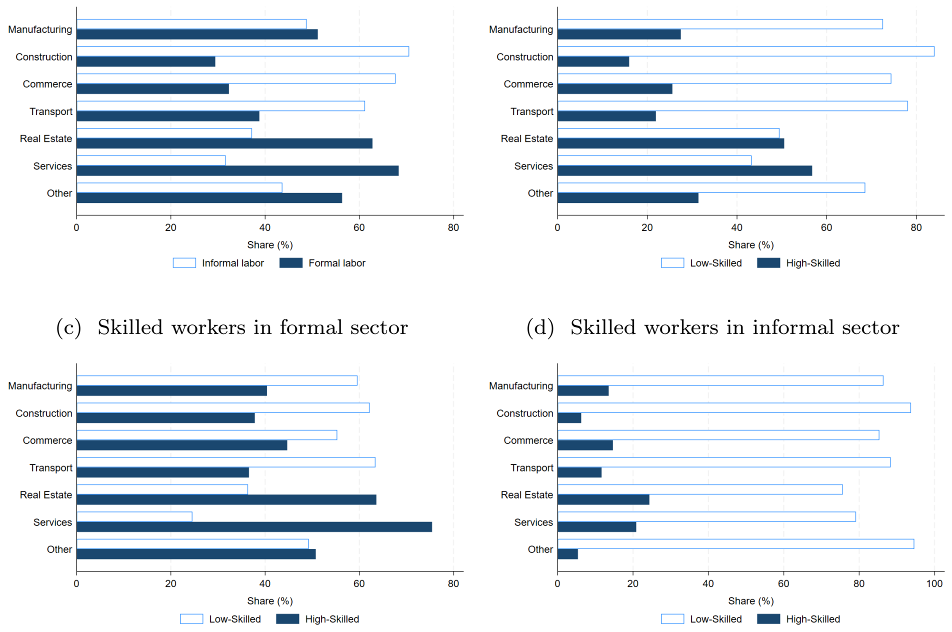
According to ENCOVI (2020), 82.2% of migrants reported that their primary reason for migrating was to find employment and improve their living conditions. In the face of this, Venezuelan migrants have dispersed across several Latin American countries, including Colombia, Peru, Ecuador, Brazil, Chile, and Argentina. Due to its geographical and cultural proximity, Colombia became the main destination for approximately 2.48 million Venezuelans between 2013 and 2023, with most settling in border regions and major urban centers (Migración Colombia, 2021). As a result, the Colombian labor market has absorbed a substantial supply shock since the onset of the Venezuelan crisis.

A particular feature of the Venezuelan migration shock is its high participation in the informal segment of the labor markets in the region. This pattern is largely explained by structural barriers, such as irregular migration status, the non-recognition of educational credentials from the country of origin, and the trade-offs between fulfilling basic subsistence needs and contributing to social security systems required for formal jobs (Bahar et al., 2021; Caruso et al., 2019; Delgado-Prieto, 2024; Peñaloza-Pacheco, 2019). Consequently, migrants are more likely to enter segments of the labor market where they directly compete with local workers, who share similar social, demographic, and economic characteristics, including age, gender, and education, among others, particularly with low-skilled, labor-intensive, and informal workers, by accepting lower wages (G. Borjas, 2003; Card, 2001; Gindling, 2009; Sinning, 2014; Theoharides, 2018; Viseth, 2020). These conditions make the informal labor market a primary channel for absorbing recent migrants, while also increasing competitive pressures on native workers occupying similar positions.

This dynamic unfolds within a Colombian labor market characterized by structural heterogeneity, with marked differences in skill composition, degrees of formality, firm size, and productive specialization across sectors. As shown in Figure 1.1a, by 2015, most employment across sectors was both informal (Panel A) and concentrated among low-skilled workers (Panel B). In that year, as the Venezuelan diaspora began to intensify, the national informality labor rate was approximately 49.7% DANE, 2022, and 87.3% of Venezuelan immigrants in Colombia were employed informally. By 2016, this rate increased to 91%, further confirming the predominance of informality as the main channel of labor market integration for newly arrived migrants.

A closer look at Panels C and D reveals that the overall skill composition within both formal and informal segments remains relatively low across most sectors. The notable exceptions are the Real Estate and Services sectors, where formal employment is predominantly composed of high-skilled workers.

Figure 1.1: The Colombian Labor Market by productive sector (2015)



(a) Formal and informal workers

(b) Occupied population

(c) Skilled workers in formal sector

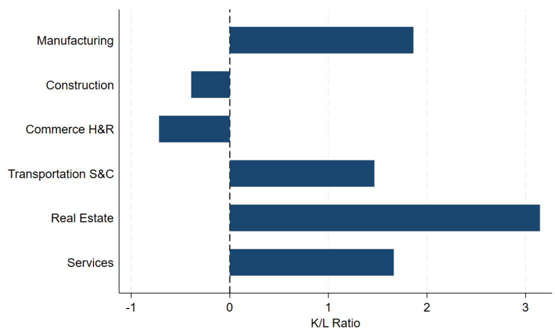
(d) Skilled workers in informal sector

I calculate data for 24 urban areas, representative of approximately 98% of the population, using sampling weights from the GEIH (2018). I consider the population between 18 and 64 years old. I calculate shares related to the entire employed population of the sample. I define High-skilled workers as the working population with 11 or more years of education, and low-skilled as the working population with less than 11 years of education. I define Formal workers as those who contribute to the social security system (health and pension); informal workers don't contribute. In Other sectors, agriculture and mining are included, as well as the public services sector. I do not take them in the analysis as my data is mainly observed at the urban level.

The use of production factors also varies substantially across sectors. As illustrated in Figure 1.2, the capital/labor ratio reveals that some sectors, such as Real Estate and Manufacturing, are by far the most capital-intensive. In contrast, sectors such as Construction and Commerce exhibit relatively lower capital intensity, indicating a more substantial reliance on labor inputs.

A hypothesis that I will develop in this work is that sector responses to exogenous labor supply shocks are mediated by their underlying production structure. In particular, labor-intensive sectors or those that predominantly employ low-skilled workers are likely to respond more directly to an influx of migrants with lower reservation wages. These dynamics can reduce overall labor costs and increase labor substitution, either between local and immigrant workers or between formal and informal employment. By contrast, capital-intensive sectors may experience more indirect effects, as labor supply shocks modify the cost structure of complementary inputs, further optimizing cost structures (Hatzigeorgiou et al., 2024; Ottaviano et al., 2018).

Figure 1.2: Capital/labor ratio (log) - 2015



Ratio is calculated in logarithms. I use department sampling weights from GEIH to construct aggregate labor. For the calculations, I use net real capital stock (base=2018), corrected for depreciation, and aggregate employment by sector at the national level. Source: GEIH and Cuentas Nacionales (DANE), 2016

In addition, the Colombian labor market is characterized by a high prevalence of micro and small firms, which account for 92% of all firms, and rely predominantly on informal labor structures and low-skilled labor (DANE, 2023). This composition reinforces the structural informality of employment, particularly in sectors with low entry barriers and high labor intensity. According to data from the *Great Integrated Household Survey* (GEIH for its acronym in Spanish), of the *National Administrative Department of Statistics* (DANE for its acronym in Spanish), between 2013 and 2019, 53% of Venezuelan immigrant workers in the country were self-employed, 43% worked informally in micro and small firms, and nearly 50% were concentrated in the Commerce sector.

In light of these conditions, the structure of Colombia's productive sectors and labor market offers a conducive environment for the integration of Venezuelan immigrants, given their specific characteristics. As highlighted by Bahar et al., 2021, even after the Colombian government implemented one of the most extensive migratory amnesty programs in the region in 2018, designed to grant regular legal status to Venezuelan migrants, the policy had no significant effect on their integration into the formal labor market. Moreover, it did not improve key labor outcomes such as wages or employability, except for marginal positive effects observed among highly educated and female workers.

1.3. Data

I use data from a repeated cross-section of the GEIH for 24 urban areas across 23 departments[2] and Bogotá D.C., representative of approximately 98% of the country's population. The analysis relies on several survey modules, including employment, labor force, migration, and individual characteristics. The characteristics module allows for the identification of informal workers, defined as those who do not contribute to the social security system (health and pension), along with their income level. Additionally, I use the labor force module to match individuals to specific productive sectors.

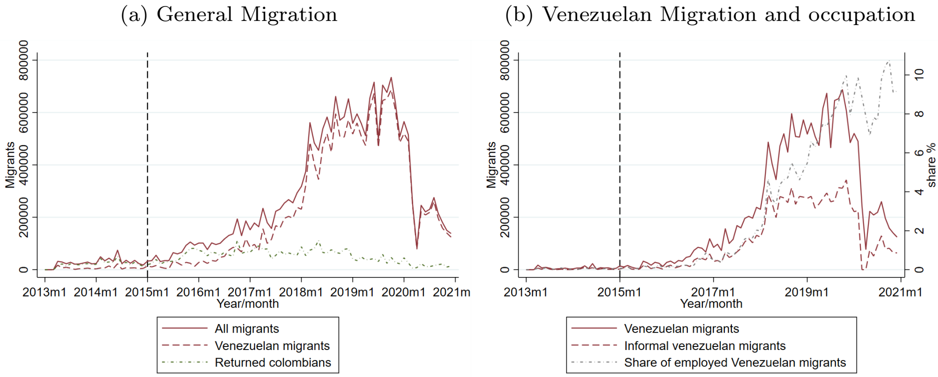
I use monthly data from the period 2013–2019, which I define based on two considerations. First, on August 19, 2015, Nicolás Maduro closed the Simón Bolívar Bridge, the main crossing point between Colombia and Venezuela, following escalating tensions caused by armed clashes between the Venezuelan military and Colombian civilians.[3] This event triggered a sharp increase in migratory flows, with nearly 700,000 Venezuelans leaving the country in search of better living conditions, primarily employment opportunities (ACNUR, 2019) (see Figure 1.3). Second, I exclude 2020 from my time period analysis to avoid confounding effects caused by

[2] Colombia is administratively divided into departments and municipalities.

[3] On September 8, 2015, Maduro also closed the second main border crossing between Zulia State and La Guajira, declared a state of emergency in three municipalities, and deployed the military to guard the territory (Tiempo, 2015).

the COVID-19 pandemic, which may have altered migration patterns for reasons unrelated to the economic and political crisis that began in 2015. Figure 1.3 depicts the dynamics of Venezuelan immigration to Colombia, showing that the period between 2015 and 2019 corresponds to the most intense phase of the inflow. This motivates the choice of these years as the core period for the empirical analysis.

Figure 1.3: Venezuelan migration shock in Colombia (2013-2020)



I calculate data for 24 urban areas representative of approximately 98% of the population, using national sampling weights from the GEIH (2013-2020). I also calculate the shares taking into account the general population and the working-age population between 18 and 65 years in urban areas. Source: GEIH (DANE) 2013-2020.

For this research, I define migrants as individuals who reported living in Venezuela 12 months prior to the survey and who were born in Venezuela, thereby excluding Colombian returnees. This distinction is crucial, as returnees may influence labor outcomes differently, either because their native networks facilitate smoother integration into the Colombian labor market or because their origin status allows them to participate under more favorable conditions than Venezuelan-born migrants. I exclude individuals who arrived from Venezuela more than 12 months but less than five years before the survey, who are neither Colombian nor Venezuelan born, and I do not classify them as either migrants, locals, or returnees. Including them in either group could introduce bias in the estimated effects. In addition, I define locals as individuals who lived in Colombia for at least 12 months before the survey, were born in Colombia, and had not lived in Venezuela for at least five years.

For the economic sector analysis, I focus on six major sectors classified according to the *International Standard Industrial Classification* (CIIU by its acronym in spanish) (DANE, 2006), as defined within each department[4], namely, Manufacturing, Construction, Commerce, Transport, Real Estate, and Services. I assume that the social and economic vulnerabilities of informal workers lead them to choose occupations across sectors with relatively low barriers to entry, as suggested by Friberg and Midtbøen (2018) and Nowotny (2012). In what follows, I demonstrate that migrants tend to settle in areas where they can rely on support networks established by previously settled peers (see Figure 1.7 in the Appendix). Under this context, migrants' occupational choices are shaped less by sector-specific dynamics within departments and more by the geographic patterns of migrant settlement across departments. In other words, spatial clustering, driven by peer networks and initial entry points, may have a more substantial influence on labor market outcomes than differences across industries within a given location.

Table 1.1 summarizes key sociodemographic and labor market characteristics of locals, Venezuelan migrants, and Colombian returnees. The descriptive patterns reveal several stylized facts that are consistent with prior empirical findings. As documented in the literature, Panel A shows that migrants have higher labor force participation and unemployment rates than locals, and a larger share of them are employed in the informal sector.

Finally, Panel C shows that, on average, Venezuelan migrants are younger and slightly more educated than the local population. Additionally, a smaller proportion of migrants identify as household heads. In contrast, Colombian returnees display demographic profiles more similar to those of locals in terms of age and household composition; however, their labor market outcomes more closely resemble those of Venezuelan migrants, particularly in terms of higher informality, unemployment rates, and lower labor force participation rates. Unlike Venezuelan migrants, returnees

[4] I exclude the agricultural sector because the sample is limited to urban areas, which could bias any observable change. I also exclude mining due to the lack of a representative migrant population in that sector.

are more likely to rely on pre-existing social networks, such as family or friends, which may facilitate their reintegration into Colombian society (Caruso et al., 2019). For this reason, I exclude them from both the migrant and local categories in the analysis.

Table 1.1: Descriptive statistics (2019)

	Locals			Migrants			Returnees		
	N	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
Panel A. Labor Force									
Participation	406,859	0.76	0.43	6,032	0.82	0.38	581	0.79	0.41
Unemployed	406,859	0.09	0.29	6,032	0.17	0.38	581	0.15	0.36
Employed	406,859	0.67	0.47	6,032	0.65	0.48	581	0.63	0.48
Formal	230,241	0.54	0.50	3,961	0.03	0.17	359	0.10	0.30
Informal	230,241	0.46	0.50	3,961	0.97	0.17	359	0.90	0.30
Panel B. Participation of informal labor by firm size									
Self-employment	145,559	0.58	0.49	3,862	0.41	0.49	330	0.54	0.50
Micro & small	145,559	0.41	0.49	3,862	0.56	0.50	330	0.41	0.49
Medium & big	145,559	0.02	0.12	3,862	0.03	0.16	330	0.05	0.21
Panel C. Demographics of informal workforce									
Age	109,439	39.30	12.65	3,862	30.72	9.57	330	43.03	11.64
Schooling years	109,439	8.4	3.92	3,862	10.52	3.45	330	8.14	3.77
Female	109,439	0.42	0.49	3,850	0.41	0.49	330	0.44	0.50
Household head	109,439	0.48	0.50	3,862	0.34	0.47	330	0.46	0.50

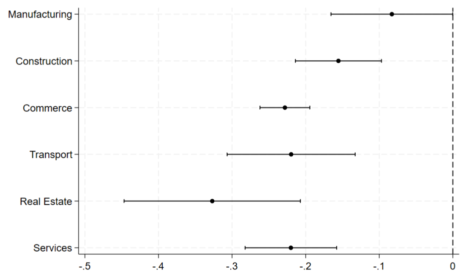
I use national weighted samples from GEIH. The measurement is restricted to the working-age population between 18 and 64 years old, which includes the labor force in general and those employed in the informal sector for 24 urban areas, representative of approximately 98% of the population. Firm size is classified according number of employments. Micro & small firms employ between 2 and 50 workers. Medium & big firms employ more than 50 workers. Source: GEIH (DANE) 2019.

On the other hand, according to Figure 1.4, in general migrants earn less and work more hours than locals. Panel A shows that the informal wage gap between migrants and native workers is largest in the Real Estate, even if the migrants are more educated than locals among all sectors (Panel C). Panel B shows that the gap in hours worked is largest for Manufacturing, Commerce and Services sectors, but for Real Estate both of them appear to work at the same intensity.

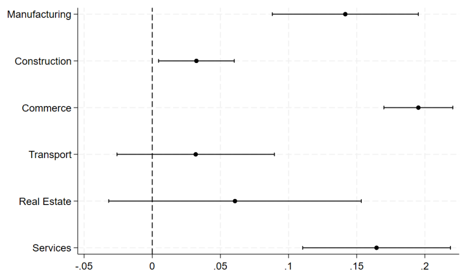
This trend is consistent with the migration literature, which emphasizes that migrants' education and work experience are often undervalued in destination countries. As a result, migrants, particularly those who have recently arrived, tend to lower their reservation wages and exhibit greater willingness to accept available jobs. Several factors contribute to this phenomenon, including irregular migration status, employers' perceptions of migrants' productivity, and the lack of host country–specific training or credentials required by the local labor market structure (Constant et al., 2016; Friedberg, 2000; Nanos and Schluter, 2014; Nowotny, 2012; Sinning, 2014).

Figure 1.4: Mean differences of wages, working hours, and schooling years of locals vs. migrants by sector (2019)

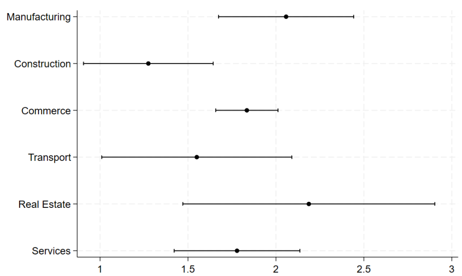
(a) Informal wages (log)



(b) Working hours of informal workers (log)



(c) Schooling years of informal workers



I calculate data for 24 urban areas representative of approximately 98% of the population, using national sampling weights from the GEIH (2013-2020). I also calculate the shares taking into account the general population and the working-age population between 18 and 65 years in urban areas. Source: GEIH (DANE) 2013-2020.

Lastly, Table 1.2 shows that migrants are most commonly employed in the Commerce, Services, and Construction sector (Panel B). It is also observed that most of the migrants who work in Transport, Real Estate, and Services are self-employed.

Additionally, micro and small firms employ a substantial share of informal workers, a pattern particularly pronounced among migrants in sectors such as Manufacturing, Construction, and Commerce. However, Panel B reveals an exception in the Real Estate sector, where 16% of migrants are informally employed by medium and big firm structures that are typically formal in nature. In this respect, Delgado-Prieto, 2024 shows that some formal firms respond to the migrant labor supply shock by employing informal workers at lower wages.

Table 1.2: Informal employment by firm size and productive sector (2019)

			Self-employment		Micro & small		Medium & big	
	N	**Share**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Panel A. Locals								
Manufacturing	12,883	0.12	0.47	0.50	0.52	0.50	0.02	0.12
Construction	11,032	0.10	0.47	0.50	0.53	0.50	0.01	0.08
Commerce	42,242	0.37	0.48	0.50	0.52	0.50	0.01	0.08
Transport	13,651	0.12	0.82	0.38	0.16	0.37	0.01	0.12
Real Estate	8,142	0.06	0.78	0.41	0.20	0.40	0.02	0.14
Services	17,781	0.16	0.75	0.43	0.21	0.41	0.04	0.19
Other	3,708	0.07	0.51	0.50	0.46	0.50	0.02	0.15
Observations	145,559							
Panel B. Migrants								
Manufacturing	405	0.10	0.25	0.43	0.71	0.45	0.04	0.20
Construction	415	0.11	0.26	0.44	0.71	0.46	0.03	0.17
Commerce	2,095	0.55	0.38	0.49	0.61	0.49	0.01	0.15
Transport	189	0.05	0.70	0.50	0.26	0.44	0.04	0.20
Real Estate	162	0.04	0.64	0.48	0.21	0.41	0.16	0.37
Services	526	0.14	0.68	0.47	0.29	0.46	0.02	0.15
Other	33	0.01	0.18	0.39	0.81	0.40	0.01	0.10
Observations	3,862							

I use national weighted samples from GEIH. The measurement is restricted to the working-age population between 18 and 64 years old, which includes the employed workers in the informal sector for 24 urban areas, representative of approximately 98% of the population. Firm size is classified according to the number of employees. Micro & small firms employ between 2 and 50 workers. Medium & large firms employ more than 50 workers. Source: GEIH (DANE) 2019.

Additionally, within each sector, the effect of migration on labor market outcomes may vary across occupational profiles. To capture this heterogeneity, I classify workers into 22 occupational categories in Table 1.9 of the Appendix, based on the 1970 *National Classification of Occupations* (CNO for its acronym in Spanish), adopted by DANE in the GEIH. Then, I group these occupations into two broad categories, namely, white-collar and blue-collar jobs (see Table 1.9 in the Appendix)[5]. This classification allows me to examine how the immigration supply shock im-

[5] White-collar jobs include professionals, managers, administrative staff, and other office-based occupations, typically requiring 11 or more years of education. Blue-collar jobs refer to manual or skilled trades performed in industrial or physical environments, typically requiring fewer than 11 years of education.

pacts informal occupational profiles, conditional on the sector in which workers are employed.

1.4. Empirical Strategy

Given that I examine the effects of migration at the productive sector level on informal wages and employment, I propose to analyze labor market shocks across sectors within departments, while accounting for local heterogeneity. This strategy acknowledges the substantial variation in productivity observed across both regions and sectors in Colombia (Arango et al., 2019; Iregui et al., 2007), as well as the heterogeneous intensity of migration supply shocks across departments (see Figure1.7 in Appendix). By adopting this sector-by-department framework, I am able to estimate the aggregate impact of the migration shock across the 24 urban areas and within the six main sectors previously defined.

To observe this relationship, I would estimate an OLS model separately for each productive sector, under the assumption that migration shocks generate heterogeneous effects depending on the sector's structural characteristics and dynamics, as specified below:

$$Y_{dt} = \delta_d + \delta_t + \beta I_{dt} + \Lambda' \Theta_{dt} + \varepsilon_{sdt} \tag{1.1}$$

Where Y_{dt} represents the informal labor market outcome of interest, defined as either the logarithm of real hourly wages of informal local workers interacted with the share of informal employment of local by productive sector within department d and year t, and the logarithm of the share of local informal workers per sector, aggregated by productive sector within department d and year t. I also include department and year fixed effects, δ_d and δ_t, respectively, to control for time-invariant regional characteristics and common temporal shocks. The term $\Lambda' \Theta_{dt}$ encompasses a set of individual-level controls for the working-age population, aggregated at the department level, including age and years of schooling.

To account for potential correlation between outcomes across sectors, I also include an input-output matrix interacted with time-varying GDP at the department-sector level. This approach highlights the interdependence among sectors, capturing the contribution of each sector that relies on inputs from others and isolating estimates of those dynamics developed in cross-border points. I cluster standard errors at the department level to account for heteroskedasticity and serial correlation within geographic units, and ε_{dt} denotes the error term.

Finally, I define the variable of interest I_{dt} as the aggregate share of Venezuelan migrants by sector, who recently arrived (12 months ago) to the country, and are employed in department d an time t (V_{dt}), related to the total employed population in each sector at the department level over time (L_{dt}). Formally:

$$I_{dt} = \frac{V_{dt}}{L_{dt}} \tag{1.2}$$

However, equation (1.1) has a key limitation related to the definition of the immigrant share. Some unobservable factors, either endogenous or idiosyncratic to migrants' decision-making, are challenging to account for. For instance, the choice of settlement location may depend on unmeasured social or economic constraints and opportunities, which in turn influence the distribution of migrants across destinations and time. This self-selection process generates considerable geographic mobility, making it challenging to isolate exogenous variation in migrant exposure.

In addition, the immigration labor supply shock may influence wages, but wages themselves can also attract migrants. This simultaneity leads to not only a self-selection problem but also a potential issue of reverse causality.

In particular, these issues may induce a covariance between the explanatory variable and the error term ($\text{Cov}(X, \varepsilon) \neq 0$), thereby violating the exogeneity assumption and leading to biased estimates. In other words, this bias arises from an unblocked backdoor path between the share of migrants and labor market outcomes, driven by unobserved idiosyncratic shocks.

Under these conditions, OLS estimates are likely to be biased and inconsistent, making it necessary to adopt an alternative identification strategy that allows me to expose the causal effect of migration shocks on labor market outcomes. To achieve this, I implement an instrumental variables (IV) approach that exploits exogenous and observable variation in migration flows to identify their impact on labor outcomes.

In settings where migrant self-selection is a concern, the literature commonly employs *shift-share* instruments (G. Borjas, 2003; Card, 2001; Dustmann et al., 2016; Jaeger et al., 2018), which predicts the geographic distribution of migrants over time based on historical settlement patterns and national-level inflows, providing a plausibly exogenous source of variation across locations and sectors.

I implement a two-stage estimation strategy. In the first stage, I verify that the instrument is strongly correlated with the endogenous variable, thereby satisfying the relevance condition. Once the instrument relevance is established, I use the second stage to identify the causal effect of the share of migrants on labor market outcomes. Formally, I instrument the endogenous migrant share as follows:

$$I_{dt} = \gamma_d + \gamma_t + \alpha \left(Ven_{2005} \times D_{kd} \times MigFlu_t \right) + \phi' \mathbf{\Gamma}_{dt} + \mu_{dt} \tag{2.1}$$

In this specification, γ_d and γ_t denote department and year fixed effects, respectively. $\mathbf{\Gamma}_{dt}$ represents the set of aggregated individual-level controls at the department level, along with the input-output matrix interacted with time-varying GDP at the department-sector level. μ_{sdt} denotes the error term.

The term in parentheses captures the labor supply of Venezuelan migrants using a *shift-share* instrument based on a triple interaction. A common concern in the migration literature regarding this type of instrument is the potential serial correlation in migration flows over time, which can lead to biased estimates (Jaeger et al., 2018; Mitze, 2019). To address this issue, I construct the instrument using historical settlement patterns of Venezuelan migrants in Colombia, as recorded in the 2005 Population Census by DANE. Specifically, I denote $Ven_{d,2005}$ as the share of Venezuelan migrants residing in department d in 2005, relative to the total population in that department for the same year. This component functions as a proxy for pre-existing migrant networks, which may influence subsequent settlement decisions by new migrants.

$$Ven_{2005} = \frac{V_{d,2005}}{L_{d,2005}} \tag{2.2}$$

On the other hand, it is important to consider that migration entails costs, and reaching distant destinations may be expensive for many migrants, which may influence their settlement decisions. Following the approach of Caruso et al. (2019), Del Carpio (2015) and Delgado-Prieto (2024), the second component of the interaction term, denoted as D_{kd}, captures the predicted number of migrants from origin state k in Venezuela who settle in department d in Colombia, conditional on the geographic distance between the two locations, as follows:

$$D_{kd} = \sum_{k} \frac{1}{T_{kd}} \times O_k \tag{2.3}$$

Where T_{kd} denotes the travel distance in kilometers from the centroid of the state k in Venezuela to the centroid of department d in Colombia, using OpenStreetMap data in QGIS. O_k denotes the share of Venezuelan migrants who migrate from origin k according to RAMV, 2018.

Finally, the third component, $MigFlu_t$, captures the annual influx of Venezuelan migrants into Colombia during the period 2015–2019, a time in which migration increased sharply, as reported by Migración Colombia, 2021. This term introduces time variation into the instrument, increasing in magnitude as the Venezuelan crisis intensifies.

With this triple interaction, I construct an instrument that distributes migration shocks both geographically across departments and temporally over time in Colombia. Under this setup, Equation (1.1) corresponds to the second stage of the estimation strategy, in which the variable I_{dt} is instrumented using the *shift-share* specification.

1.5. Results

1.5.1. At the productive sector level

First of all, Panel C of Table 1.3 shows with first-stage estimates that the instrument is quite predictive of the share of migrants, indicating that it has the power to explain exogenously the effect on labor market outcomes in a generous manner, judging by the held values of R-squared.

Overall, Panel A reveals a statistically significant decline in informal hourly wages for native workers in response to the migration shock. Hourly wages across all sectors exhibit heterogeneous responses. Overall, a one percentage point increase in the share of Venezuelan migrants is associated with a 0.04% reduction in hourly informal wages. Specifically, the wage drops are statistically significant in the Construction, Commerce (slightly), Real Estate, and Services sectors, for which migrants' representation is considerable.

In contrast, Panel B shows that the impact on locals' informal employment is more sector-specific, with the most substantial effect observed in both the Construction and Services sectors, resulting in a decrease of 0.06% and 0.03% per one-percentage point increase in the participation of employed migrants.

Table 1.3: Venezuelan migration and the informal labor market by sector

	All sectors	Manufac.	Construc.	Commerce	Transport	Real Estate	Services
Panel A. Informal hourly wages							
OLS							
Share of migrants	-0.027***	0.004	-0.066**	-0.007	-0.016	-0.062**	-0.014
	(0.009)	(0.022)	(0.024)	(0.013)	(0.032)	(0.027)	(0.022)
2SLS							
Share of migrants	-0.040***	0.007	-0.101***	-0.019*	-0.023	-0.066***	-0.048***
	(0.006)	(0.028)	(0.031)	(0.011)	(0.029)	(0.018)	(0.016)
Panel B. Informal employment							
OLS							
Share of migrants	-0.005	0.015	-0.047**	0.002	0.010	0.000	-0.009
	(0.004)	(0.020)	(0.017)	(0.006)	(0.014)	(0.028)	(0.012)
2SLS							
Share of migrants	-0.009**	0.042	-0.057**	0.004	0.006	-0.014	-0.031***
	(0.004)	(0.029)	(0.023)	(0.007)	(0.015)	(0.022)	(0.007)
Panel C. First-stage							
Share of migrants							
$\text{Ven}_{2005} \times \text{D}_{kd}$	0.223***	0.212***	0.224***	0.226***	0.219***	0.217***	0.229***
$\times \text{MigFlu}_t$	(0.017)	(0.016)	(0.019)	(0.017)	(0.020)	(0.016)	(0.019)
R^2	0.90	0.91	0.90	0.90	0.90	0.92	0.90
Kleibergen-Paap F	134.6	132.6	113.4	131.9	92.94	151.8	112.2
Obsservations	720	120	120	120	120	120	120

Dependent variables are the logarithm of real hourly wages of informal local workers, interacted with the share of informal employment of local workers by sector (Panel A) and the logarithm of the share of local informal workers per sector (Panel B), both measured at the department/sector/year level. Each cell reports the regression of the variable in the row by the model in the column, and the coefficients are already multiplied by 100. Standard errors clustered at the department level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). All regressions include department and year fixed effects. The regression for the full sample (All sectors) includes sector × department fixed effects. Control variables include 2018 population × year dummies, and the output-input matrix × time-varying GDP by department and sector level. I use national weighted samples from the GEIH.

As depicted before, the Manufacturing, Real Estate, and Services sectors exhibit a higher proportion of formal workers compared to other sectors. Panel A of Table 1.4 shows that although the general impact on formal wages is not significant, as shown in studies such as Bahat et al. (2021), Caruso (2019), Del Carpio (2015), and Santamaria (2022), I observe slightly significant and less pronounced effects on Real Estate and Services, where the proportion of high-skill workers is larger. However, I do not find statistically significant changes in formal employment, nor any effect on the Manufacturing sector.

Table 1.4: Venezuelan migration and the formal labor market by sector

	All sectors	Manufac.	Construc.	Commerce	Transport	Real Estate	Services
Panel A. Formal hourly wages							
OLS							
Share of migrants	-0.020	0.019	-0.048	-0.033	-0.012	-0.065**	0.020
	(0.015)	(0.027)	(0.071)	(0.037)	(0.024)	(0.028)	(0.022)
2SLS							
Share of migrants	-0.019	0.006	-0.010	-0.025	-0.018	-0.048**	-0.021*
	(0.023)	(0.026)	(0.069)	(0.036)	(0.019)	(0.023)	(0.011)
Panel B. Formal employment							
OLS							
Share of migrants	-0.025	0.011	-0.046	-0.044	-0.007	-0.098**	0.036*
	(0.015)	(0.035)	(0.070)	(0.039)	(0.020)	(0.036)	(0.019)
2SLS							
Share of migrants	-0.005	0.022	0.012	-0.010	-0.003	-0.045	-0.006
	(0.018)	(0.015)	(0.060)	(0.031)	(0.012)	(0.031)	(0.013)
Panel C. First-stage							
Share of migrants							
$Ven_{2005} \times D_{kd}$	0.223***	0.212***	0.224***	0.226***	0.219***	0.217***	0.229***
$\times MigFlu_t$	(0.017)	(0.016)	(0.019)	(0.017)	(0.020)	(0.016)	(0.019)
R^2	0.90	0.91	0.90	0.90	0.90	0.92	0.90
Kleibergen-Paap F	134.6	132.6	113.4	131.9	92.94	151.8	112.2
Obsservations	720	120	120	120	120	120	120

Dependent variables are the logarithm of real hourly wages of formal local workers interacted with the share of formal employment of locals by sector (Panel A) and the logarithm of the share of local former workers per sector (Panel B), both measured at the department/sector/year level. Each cell reports the regression of the variable in the row by the model in column, and coefficients are already multiplied by 100. Standard errors clustered at the department level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). All regressions include department and year fixed effects. The regression for the full sample (All sectors) includes sector × department fixed effects. Control variables include 2018 population × year dummies, and the output-input matrix × time-varying GDP by department and sector level. I use national weighted samples from the GEIH.

1.5.2. At the job-occupation level

As mentioned, effects on informal labor outcomes may be driven by low-skilled or labor-intensive jobs. Building on the previous results, Panel A of Table 1.5 shows that wage responses among blue-collar jobs (BC), typically associated with low-skilled workers, are negative and statistically significant in several sectors. Overall, the labor supply shock has an impact on BC informal hourly wages, with an average decline of 0.05%, driven primarily by the Construction, Commerce, and Real Estate sectors. In contrast, wage reductions among White collar (WC) workers are not statistically significant.

An important consideration in interpreting these effects is the occupational composition within each sector. Both wage and employment responses observed among blue-collar workers appear to be conducted by occupations that are overrepresented among informal employees (see Table 1.9 in the Appendix). For instance, in the case of the Real Estate sector, cleaning and security personnel jobs account for a substantial share of informal employment, for Construction, there is a high participation of bricklayers and manual laborers, and for Commerce, there is a large proportion of independent sellers, store employees, and food processing workers.

Furthermore, Panel B shows that the impact on informal employment is limited among white-collar occupations, with no significant effects observed. But, among blue-collar jobs, the most substantial negative effect on informal employment is also found in the Construction sector.

Table 1.5: Venezuelan migration and informal labor outcomes by job profile at the productive sector level

	All sectors	Manufac.	Construc.	Commerce	Transport	Real Estate	Services
Panel A. Informal hourly wages							
				White-Collar jobs			
OLS							
Share of migrants	0.005	0.093	0.088	0.004	-0.139*	-0.044	0.028
	(0.028)	(0.082)	(0.132)	(0.042)	(0.075)	(0.038)	(0.034)
2SLS							
Share of migrants	0.030	0.079	0.102	0.009	0.068	-0.004	-0.001
	(0.029)	(0.064)	(0.107)	(0.031)	(0.058)	(0.031)	(0.040)
				Blue-collar jobs			
OLS							
Share of migrants	-0.036***	-0.026	-0.074***	-0.015	-0.017	-0.085*	0.003
	(0.011)	(0.023)	(0.025)	(0.014)	(0.029)	(0.045)	(0.024)
2SLS							
Share of migrants	-0.050***	-0.014	-0.138***	-0.027**	-0.024	-0.096***	-0.004
	(0.009)	(0.027)	(0.032)	(0.012)	(0.031)	(0.027)	(0.020)
Panel B. Informal employment							
				White-collar jobs			
OLS							
Share of migrants	0.004	0.029	0.040	-0.015	-0.017	-0.041	0.028*
	(0.023)	(0.066)	(0.108)	(0.032)	(0.039)	(0.025)	(0.016)
2SLS							
Share of migrants	0.002	-0.001	0.026	0.020	-0.011	-0.024	0.001
	(0.018)	(0.034)	(0.074)	(0.025)	(0.038)	(0.021)	(0.011)
				Blue-collar jobs			
OLS							
Share of migrants	-0.009	0.004	-0.045*	-0.008	0.010	-0.027	0.015
	(0.006)	(0.024)	(0.022)	(0.008)	(0.020)	(0.036)	(0.018)
2SLS							
Share of migrants	-0.012***	0.036	-0.073***	-0.003	-0.001	-0.039	-0.002
	(0.005)	(0.032)	(0.027)	(0.009)	(0.019)	(0.024)	(0.012)
Panel C. First-stage							
Share of migrants							
$\text{Ven}_{2005} \times D_{kd}$	0.223***	0.212***	0.224***	0.226***	0.219***	0.217***	0.229***
$\times \text{MigFlu}_t$	(0.017)	(0.016)	(0.019)	(0.017)	(0.020)	(0.016)	(0.019)
R^2	0.90	0.91	0.90	0.90	0.90	0.92	0.90
Kleibergen-Paap F	134.6	135.1	103.3	134.1	100.3	194.4	119.2
Observations	720	120	120	120	120	120	120

Dependent variables are the logarithm of real hourly wages of informal local workers interacted with the share of informal employment of local by sector (Panel A) and the logarithm of the share of local workers per sector (Panel B), both measured at the department/sector/year level for white-collar and blue-collar jobs. Each cell reports the regression of the variable in the row by the model in the column, and the coefficients are already multiplied by 100. Standard errors clustered at the department level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). All regressions include department and year fixed effects. The regression for the full sample (All sectors) additionally includes sector fixed effects. Control variables include 2018 population × year dummies, and the output-input matrix × time-varying GDP by department and sector level. I use national weighted samples from the GEIH.

1.5.3. At the firm size level

As previously discussed, informal workers are predominantly concentrated in low-productivity structures such as micro and small firms, as well as in self-employment, which increases their vulnerability to labor substitution and downward pressure on wages. Panel A of Table 1.6 shows that self-employed workers experience the most pronounced wage declines across nearly all sectors, with particularly strong effects in Construction, for each one-percentage-point increase in the share of employed Venezuelan migrants, informal hourly wages among the local self-employed fall by approximately 0.14%, and by 0.11% among workers in micro firms. In the Commerce sector, wage reductions are observed exclusively among informal employees in small firms. A particularly consistent pattern emerges in the Real Estate sector, where informal wages decline across all firm sizes. The effect is especially pronounced in small firms, with wages decreasing by 0.28% for each one-percentage-point increase in migrant participation.

In terms of employability, Panel B reveals that declines in informal employment are most pronounced within micro and small firms. At the sectoral level, these reductions are primarily driven by the Construction sector, both among the self-employed and those working in small firms, as well as by the Transport sector in the self-employment and micro-firm segments, and by the Services sector within small firms. These patterns are consistent with previous findings that highlight a high concentration of blue-collar and low-skilled occupations in these sectors, making them particularly susceptible to labor displacement effects in the face of migration shocks.

These outcomes can also be understood through the lens of occupational mismatch and substitution dynamics documented in the literature. Studies by Caruso et al. (2019) and Delgado-Prieto (2024) for the case of Venezuelan immigrants in Colombia, and Olivieri et al. (2021) in Ecuador, show that migration flows often lead to skill mismatches in the host labor market, whereby qualified workers, unable to validate credentials or access suitable jobs, enter occupations that do not align with their training. As described by Nowotny (2012), this "brain waste" phenomenon reflects migrants' willingness to accept lower-skilled positions in exchange for labor market access or relatively higher earnings. From the firms' perspective, this scenario generates strong incentives to substitute capital with lower-cost labor by hiring overqualified migrants at suppressed wages, particularly in low-productivity sectors.

Table 1.6: Venezuelan migration and informal wages by firm size at the productive sector level

	All sectors	Manufac.	Construc.	Commerce	Transport	Real Estate	Services
Panel A. Informal wages							
				Self-employed workers			
OLS							
Share of migrants	-0.037**	-0.004	-0.116*	-0.006	-0.025	-0.056*	-0.016
	(0.014)	(0.041)	(0.065)	(0.021)	(0.027)	(0.028)	(0.040)
2SLS							
Share of migrants	-0.060***	-0.068**	-0.143***	0.002	-0.057***	-0.035*	-0.040*
	(0.009)	(0.027)	(0.036)	(0.019)	(0.019)	(0.021)	(0.024)
				Micro firms			
OLS							
Share of migrants	-0.029	-0.020	0.035	-0.006	-0.052	-0.157*	0.024
	(0.032)	(0.033)	(0.085)	(0.016)	(0.089)	(0.077)	(0.044)
2SLS							
Share of migrants	-0.064***	0.018	-0.111**	-0.013	-0.195**	-0.143***	0.048
	(0.024)	(0.053)	(0.044)	(0.016)	(0.085)	(0.053)	(0.033)
				Small firms			
OLS							
Share of migrants	-0.034	0.014	-0.016	-0.053	-0.115	-0.152	0.116*
	(0.027)	(0.067)	(0.052)	(0.036)	(0.154)	(0.130)	(0.063)
2SLS							
Share of migrants	-0.042**	0.029	-0.042	-0.032*	-0.045	-0.278**	0.066
	(0.017)	(0.075)	(0.039)	(0.019)	(0.101)	(0.123)	(0.058)
Panel B. Informal employment							
				Self-employed workers			
OLS							
Share of migrants	-0.012	0.023	-0.080	-0.015	0.003	-0.013	0.011
	(0.008)	(0.035)	(0.052)	(0.020)	(0.018)	(0.031)	(0.024)
2SLS							
Share of migrants	-0.028***	-0.019	-0.082**	0.003	-0.027*	-0.029	-0.003
	(0.005)	(0.026)	(0.035)	(0.016)	(0.015)	(0.023)	(0.017)
				Micro firms			
OLS							
Share of migrants	-0.018	-0.012	0.047	0.015	-0.078	-0.036	-0.047
	(0.023)	(0.041)	(0.074)	(0.012)	(0.055)	(0.049)	(0.029)
2SLS							
Share of migrants	-0.047***	0.017	-0.049	0.017*	-0.175***	-0.093**	-0.006
	(0.017)	(0.058)	(0.044)	(0.009)	(0.049)	(0.037)	(0.021)
				Small firms			
OLS							
Share of migrants	-0.033*	-0.006	-0.070	-0.040	-0.080	-0.029	0.026
	(0.019)	(0.063)	(0.054)	(0.033)	(0.115)	(0.096)	(0.047)
2SLS							
Share of migrants	-0.042***	0.033	-0.136***	0.002	-0.017	-0.105	-0.081***
	(0.010)	(0.066)	(0.039)	(0.017)	(0.086)	(0.095)	(0.028)
Panel C. First-stage							
Share of migrants							
$\text{Ven}_{2005} \times \text{MigFlu}_t$	0.223***	0.178***	0.281***	0.317***	0.162***	0.122***	0.174***
$\times\ \text{D}_{kd}$	(0.018)	(0.025)	(0.052)	(0.026)	(0.011)	(0.012)	(0.019)
R^2	0.729	0.82	0.76	0.94	0.84	0.75	0.87
Kleibergen-Paap F	117.8	138.1	107	113.7	65.13	172.2	86.63
Observations	720	120	120	120	120	120	120

Dependent variables are the logarithm of real hourly wages of informal local workers interacted with the share of informal employment of local by sector (Panel A) and the logarithm of the share of local workers per sector (Panel B), both measured at the department/sector/year level for self-employed and employees in firms with less of 20 workers and more than 20 workers. Each cell reports the regression of the variable in the row by the model in the column, and the coefficients are already multiplied by 100. Standard errors clustered at the department level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). All regressions include department and year fixed effects. The regression for the full sample (All sectors) additionally includes sector fixed effects. Control variables include 2018 population × year dummies, and the output-input matrix × time-varying GDP by department and sector level. I use national weighted samples from the GEIH.

In light of the observed decreases in employment and wages within certain firm structures in specific sectors, I examine the potential impact of migrant labor participation on sector-level productivity. A growing body of literature has documented that migration can positively influence the productivity of host economies. However, these gains tend to materialize only when migrants possess sufficiently high skill levels (G. J. Borjas, 2019; Cooray, 2014; D'Auria et al., 2008; Kahanec and Pytlikova, 2017; Manole et al., 2017; Orefice, 2010; Pouliakas et al., 2014; Tondl and Huber, 2012).

In the case of Colombia, Table 1.7 shows that Venezuelan migration has no significant effects on sectoral productivity. This result likely reflects the fact that the majority of Venezuelan immigrants are competing in the low-skilled segment, predominantly employed in less productive segments of the informal labor market. As such, their contribution may not be sufficient to generate observable productivity improvements at the aggregate sector level.

Table 1.7: Venezuelan migration and productivity by sector

	All sectors	Manufac.	Construc.	Commerce	Transport	Real Estate	Services
Panel A. 2SLS							
OLS							
Share of migrants	-0.011	0.048	-0.002	-0.009	-0.004	-0.036	-0.037
	(0.015)	(0.051)	(0.008)	(0.012)	(0.004)	(0.053)	(0.042)
2SLS							
Share of migrants	0.002	-0.050	0.004	0.003	0.000	-0.004	0.023
	(0.015)	(0.054)	(0.008)	(0.004)	(0.003)	(0.038)	(0.034)
Panel B. First stage							
Share of migrants							
$\text{Ven}_{2005}\times \text{MigFlu}_t$	0.230***	0.227***	0.229***	0.231***	0.229***	0.227***	0.232***
D_{kd}	(0.019)	(0.017)	(0.020)	(0.019)	(0.025)	(0.015)	(0.022)
R^2	0.89	0.91	0.89	0.89	0.88	0.91	0.89
Kleibergen-Paap F	143.7	142.4	108.6	116	66.94	174.6	88.81
Observations	720	120	120	120	120	120	120

Dependent variable is the productivity index, calculated with the real GDP related to the total working hours × occupied population by department and sector. Each cell represents the regression of the variable in the row by the model in the column. I cluster at the department level. I use national weighted samples from GEIH and year and department × sector fixed effects. For the *All sector* regression. I control for 2018 population × year dummies. Confidence intervals of 95% are used. *** p<0.01, ** p<0.05, * p<0.1.

Lastly, I examine whether the intensity of weekly working hours among informal local workers changes in response to the migration shock. As previously illustrated in Figure 1.4b, the presence of migrants is generally associated with an increase in weekly working hours. However, the magnitude of this effect varies across sectors. Table 1.8 confirms this pattern, a one-percentage-point increase in the share of Venezuelan migrants in the labor market is associated with a 0.02% increase in the weekly working hours of informal local workers. This effect is primarily driven by the Manufacturing and Commerce sectors, which also have the highest levels of migrant participation.

Table 1.8: Venezuelan migration and weekly working hours (log)

	All sectors	Manufac.	Construc.	Commerce	Transport	Real Estate	Services
Panel A. 2SLS							
OLS							
Share of migrants	0.007	-0.001	-0.039**	0.010	0.030**	-0.021	0.006
	(0.006)	(0.031)	(0.018)	(0.010)	(0.014)	(0.025)	(0.018)
2SLS							
Share of migrants	0.017***	0.067**	-0.043	0.027***	0.043	-0.000	-0.013
	(0.005)	(0.029)	(0.027)	(0.009)	(0.028)	(0.027)	(0.011)
Panel B. First stage							
Share of migrants							
$\text{Ven}_{2005} \times \text{MigFlu}_t$	0.230***	0.227***	0.229***	0.231***	0.229***	0.227***	0.232***
D_{kd}	(0.019)	(0.017)	(0.020)	(0.019)	(0.025)	(0.015)	(0.022)
R^2	0.89	0.91	0.89	0.89	0.88	0.91	0.89
Kleibergen-Paap F	117	151.5	101.2	75.93	71.90	187.7	81.70
Observations	720	120	120	120	120	120	120

Dependent variable is the logarithm (log) of the weekly working hours of informal local workers by department/year/sector. Each cell represents the regression of the variable in the row by the model in the column. I cluster at the department level. I use national weighted samples from GEIH and year and department × sector fixed effects. For the *All sector* regression. I control for 2018 population × year dummies. Confidence intervals of 95% are used. *** p<0.01, ** p<0.05, * p<0.1.

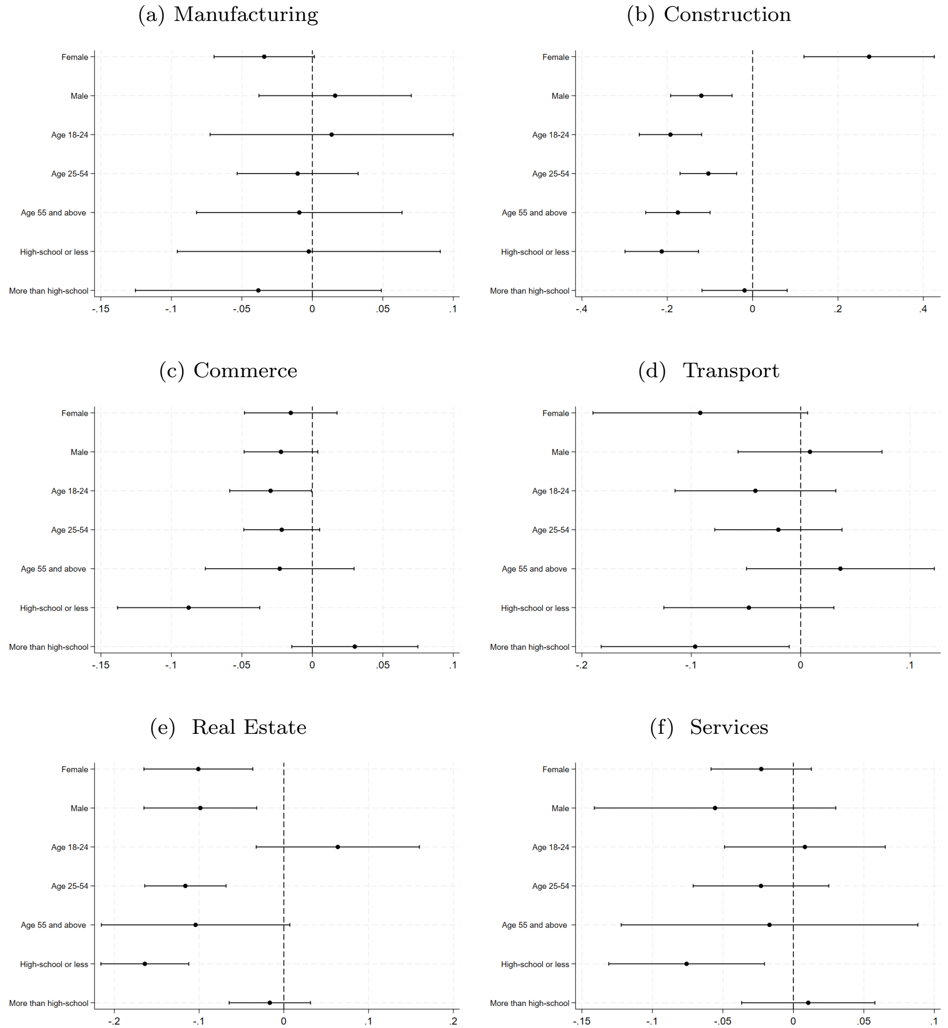
1.6. Heterogeneous effects

Figures 1.5 and 1.6 present the heterogeneous effects of migration on informal labor outcomes for local workers across different sub-population groups. Overall, most subgroups experience declines in both hourly wages and employment across sectors, although the magnitude and direction of these effects vary by demographic and skill profile. In the Manufacturing sector, females suffer a significant decline in wages, and informal employment increases for men. In contrast, the Construction sector exhibits consistent wage declines across all groups, but an exceptional increase on female wages. However, when it comes to employment, females in that sector are negatively affected by the shock. In commerce, wages decline for the less educated, particularly in sectors such as real estate and services.

When examining age groups, all of them simultaneously experience significant wage declines in Construction, but the youngest and the oldest are the ones who experience the most significant declines in employment for the sector. In the Real Estate industry, the hourly wages of middle-aged workers are the most adversely affected. Regarding employment responses, declines are more pronounced among the youngest and the oldest workers in Construction.

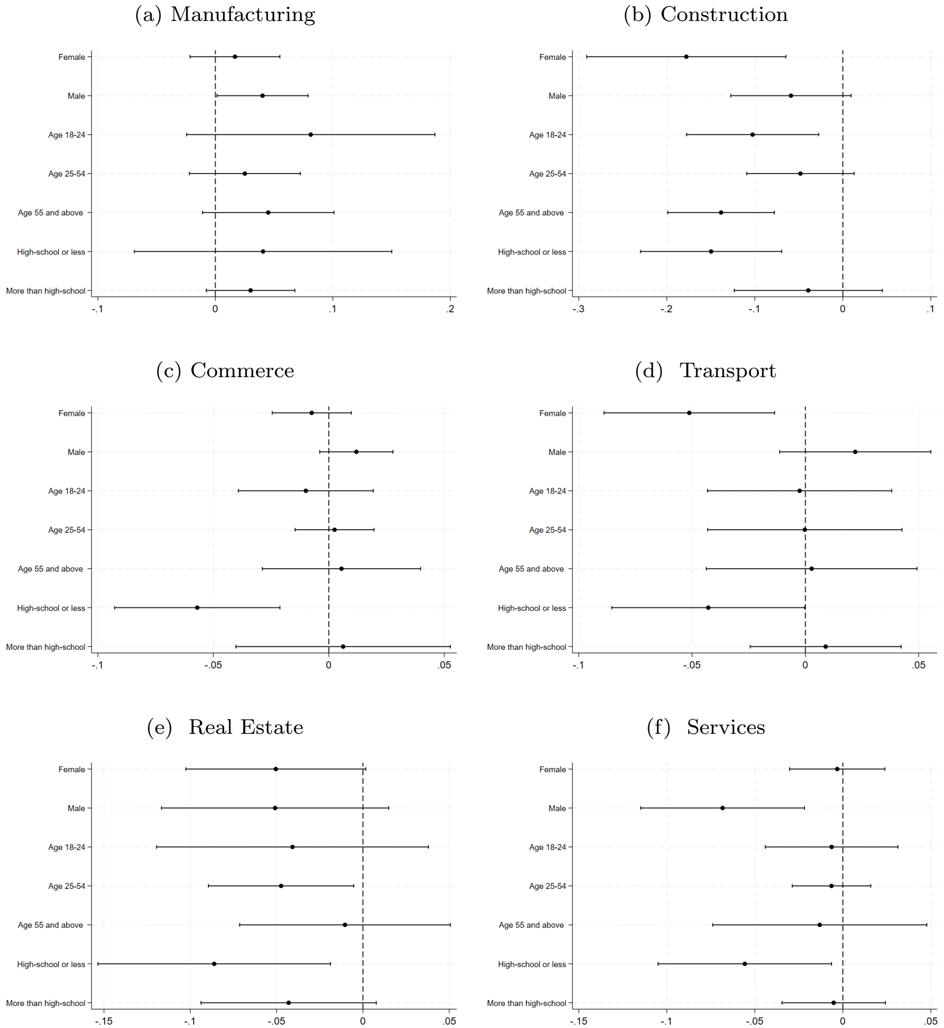
Finally, when disaggregating by education level, both wage and employment losses are predominantly concentrated among workers with lower levels of schooling among almost all sectors, which is consistent with the findings across WC and BC roles in Table 1.5.

Figure 1.5: Heterogeneous effects of Venezuelan immigration on informal wages of locals by productive sector



I calculate data for 24 urban areas, representative of approximately 98% of the population, using sampling weights from the GEIH (2018). I consider the population between 18 and 64 years old. I calculate shares related to the entire employed population of the sample. I define High-skilled workers as the working population with 11 or more years of education, and low-skilled as the working population with less than 11 years of education. I define Formal workers as those who contribute to the social security system (health and pension); informal workers don't contribute. In Other sectors, agriculture and mining are included, as well as the public services sector. I do not take them in the analysis as my data is mainly observed at the urban level.

Figure 1.6: Heterogeneous effects of Venezuelan immigration on informal employment of locals by productive sector



I calculate data for 24 urban areas, representative of approximately 98% of the population, using sampling weights from the GEIH (2018). I consider the population between 18 and 64 years old. I calculate shares related to the entire employed population of the sample. I define High-skilled workers as the working population with 11 or more years of education, and low-skilled as the working population with less than 11 years of education. I define Formal workers as those who contribute to the social security system (health and pension); informal workers don't contribute. In Other sectors, agriculture and mining are included, as well as the public services sector. I do not take them in the analysis as my data is mainly observed at the urban level.

1.7. Robustness checks

To assess the robustness of the main estimates, I perform several sensitivity checks. As a first exercise, I exclude the border departments between Colombia and Venezuela (Boyacá, Cesar, La Guajira, and Norte de Santander). This restriction helps ensure that early settlement patterns or migration spillovers do not disproportionately drive the results in these areas, which may operate under different labor market dynamics. Figures 1.8a and 1.8b in the Appendix show that, in general, the main wage and employment effects remain unchanged.

Second, the estimated effects could be sensitive to the specific baseline year used to capture historical migrant settlements. To ensure that the results are not driven exclusively by the 2005 census data, I re-estimate the model using the 1993 Population Census as the basis for constructing migrant networks. As shown in Figure 1.9, this alternative specification allows me to confirm that the results are robust to different definitions of historical settlement patterns.

Finally, one might be concerned that pre-existing departmental characteristics, such as safety, quality of public services, local economic dynamics, or public spending, could influence both migration patterns and labor market outcomes, thereby confounding the identification strategy. To address this, I test for the presence of differential pre-trends across departments. Figure 1.10 shows that the evolution of migration is not systematically related to pre-treatment characteristics at the departmental level. The proposed instrument remains a strong predictor of migrant inflows, even after accounting for these pre-trends, supporting its validity for causal inference.

1.8. Discussion and conclusions

The Venezuelan diaspora constitutes one of the most significant demographic phenomena in recent Latin American history. The socioeconomic vulnerabilities of Venezuelans prompted a massive migration to improve their living conditions, leading to an increase in the labor supply for recipient countries. Colombia is its main recipient, but the higher informality rates characterized by a low-skilled workforce generate a challenging scenario for the dynamics of its labor market. Migrants compete with their local peers by offering lower reservation wages, which triggers downward pressure on informal wages, even if they arrive in the destination country with high skills or education levels.

This study yields three main findings. First, the effects of Venezuelan migration on informal hourly wages and employment are heterogeneous across sectors. Wages and employment responses vary in elasticity to the shocks, leading in some cases to a substitution dynamic between migrants and local workers, particularly among the low-skilled segment. These substitution effects are most pronounced in the Construction, Commerce, and Real Estate sectors. Moreover, the case of Real Estate is especially notable due to the high concentration of low-skilled occupations such as cleaning and security services.

A potential explanation for this result is that migrants experience higher job separation rates, which reinforces downward pressure on wages and intensifies substitution effects for local workers across sectors, particularly in those with high migrant concentration (Caruso et al., 2019; Nanos and Schluter, 2014), such as for the low-skilled workers in Construction, Commerce and Services sectors. In this respect, immigrants are often willing to accept lower wages than natives, even when they possess similar productivity levels and occupy the same types of jobs. This phenomenon, commonly referred to as the "migration effect", is associated with their higher unemployment rates, as shown in Table 1.1.

Second, the evidence suggests that micro and small firms respond strategically to the labor supply shock by hiring migrants at lower wages, especially in the Construction, Real Estate, and Services sectors. These firms, which often operate with low to medium productivity levels and limited regulatory oversight, appear to absorb migrant labor as a cost-reduction strategy. This mechanism is consistent with findings by Delgado-Prieto (2024) and Borjas (2014), and also reinforces the fact that I do not observe significant effects on productivity at the sector level.

Last, a third point relates to the use of factors and the effects of migration.

As depicted in Figure 1.2, most of the sectors are capital-intensive; however, I find declines in both wages and employment for the Real Estate sector, the most capital-intensive among all. That is, the effects in this sector, highly intensive in capital, are driven by labor-intensive roles. That is why I find that BC roles are the most affected, and WC do not show a significant response to the labor supply shock.

The particular case of Venezuelan immigration to Colombia presents two defining characteristics. First, Venezuelan migrants were forcibly displaced due to severe economic and political conditions in their country of origin. This displacement disproportionately affected vulnerable populations, many of whom arrived in Colombia without the resources to immediately access formal employment, contributing to high unemployment rates among migrants in the host country. Second, these migrants primarily compete in a segment of the labor market dominated by low-skilled and informal occupations. Because entry barriers in this segment are relatively low, the arrival of a large pool of migrants willing to accept lower wages facilitates their rapid insertion.

However, as shown in Figure 1.1c, most sectors, regardless of formality composition, are predominantly composed of low-skilled labor. The exceptions are the Real Estate and Services sectors, where formal employment is primarily concentrated among high-skilled workers. Interestingly, I find modest but statistically significant declines in formal wages in these two sectors, yet no significant changes in formal employment. Under this context, even in segments of the formal labor market with higher skill intensity, the migration shock may exert some wage pressure without necessarily leading to job displacement, possibly due to greater rigidity in formal contracts or the Minimum Wage threshold.

In light of these findings, the analysis holds important implications for the design of differentiated public policies in response to labor supply shocks. Given that the Colombian labor market is predominantly informal and composed of low-skilled workers, targeted interventions are needed to mitigate the adverse effects of large-scale migration. My results provide a framework for policies that promote the inclusion of migrants into formal and regulated labor market segments, while simultaneously investing in human capital development to reduce vulnerability among both local and immigrant workers. Moreover, the evidence of this work highlights that a large share of the Colombian workforce remains highly exposed to displacement risks, particularly in sectors where informal, low-skilled, and labor-intensive occupations dominate, such as the Construction and Real Estate sectors, and where migrants can more easily compete by accepting lower wages.

1.A Appendix

1.A.1.

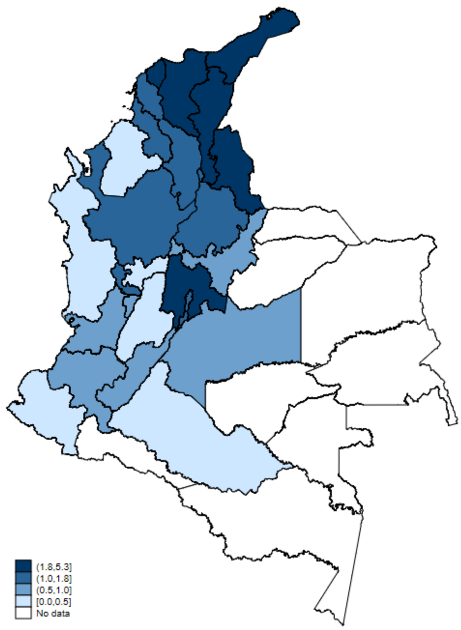
Table 1.9: White-collar and Blue-collar jobs participation by productive sector - Informal employment (2018)

Job profile	Manufac	Construc.	Commerce	Transport	Real Estate	Services
Panel A. White collar jobs						
Administrative agents	8.04	13.09	18.79	11.48	20.67	6.83
Administrative supervisors	52.23	4.86	47.94	23.85	5.20	7.54
Entertainment workers	3.40	0.00	2.06	0.04	4.25	9.54
Financial workers	10.79	8.45	13.97	4.93	26.19	2.72
Healthcare professionals	0.96	0.01	0.17	0.00	0.19	3.81
Scientists and related	17.08	65.99	11.23	4.93	32.69	28.69
Secretaries and typists	3.38	3.63	1.72	51.63	5.47	3.08
Service workers not classified	4.11	2.85	4.27	6.46	4.34	37.80
Observations	749	286	3,647	1,778	2,730	4,525
Panel B. Blue-collar jobs						
Agricultural workers	0.16	0.00	0.20	0.05	0.27	0.27
Cleaning and security workers	0.62	0.49	1.38	1.53	78.91	57.31
Sellers (Independent/employees)	8.31	0.08	59.60	0.94	7.03	6.02
Bricklayers and manual laborers	2.48	91.26	1.02	0.17	1.20	0.06
Drivers, couriers, and storage	3.25	0.99	2.99	95.86	2.99	2.17
Electricians and electronics tech.	0.11	4.94	1.67	0.39	1.67	0.13
Food processing workers	24.06	0.07	21.32	0.03	0.44	1.61
Hairdressers and beauty specialists	0.05	0.01	0.01	0.00	0.04	30.24
Machine technicians and operators	29.34	1.73	7.31	0.08	0.39	0.18
Miners and stonecutters	0.00	0.00	0.00	0.02	0.00	0.00
Sculptors/glassmakers/craftsmen	10.74	0.20	0.60	0.00	6.61	1.12
Tailors and dressmakers	20.47	0.01	1.46	0.11	0.13	0.02
Unskilled laborers not classified	0.40	0.20	2.44	0.68	0.32	0.88
Observationd	13,708	12,505	45, 543	13,261	6,612	14,731

I use CIIU classification. I calculate percentages with weighted sample, as a proportion of informal workers, including migrants. I define white-collar jobs as those performed in offices and requiring mental rather than physical effort, and blue-collar jobs as their opposite. Source GEIH-DANE (2018)

1.A.2.

Figure 1.7: Share of employed Venezuelan migrants (2019)

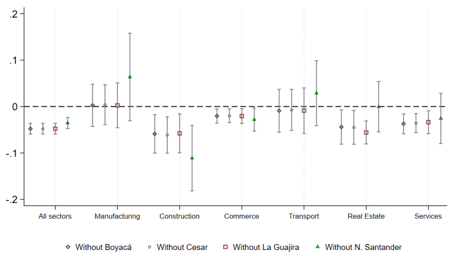


I use weighted samples to calculate the share (%) of employed Venezuelan migrants who reported arriving in Colombia within the past 12 months, relative to the total population of 24 urban areas, representative of 98% of the total population in the country. Source: GEIH-DANE, 2019

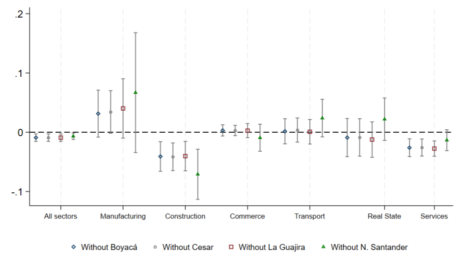
1.A.3.

Figure 1.8: Robustness test: Excluding main border cities

(a) wages of informal employment



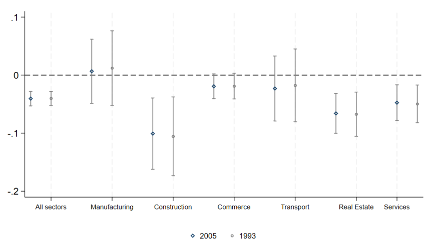
(b) local informal employment



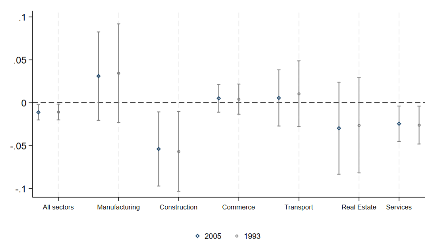
Dependent variables are the logarithm of real hourly wages of informal local workers (Panel A) and the logarithm of the number of informal local workers (Panel B), both measured at the department/sector/year level. Each estimate reports a different regression of the variables, taking out each department. Standard errors clustered at the department level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). All regressions include department and year fixed effects. The regression for the full sample (All sectors) additionally includes sector fixed effects. Control variables include age, education level, 2018 population × year dummies, and the output-input matrix × time-varying GDP by department and sector level. I use national weighted samples from the GEIH.

Figure 1.9: Robustness test: Venezuelans past settlement in 2005 vs. 1993

(a) wages of informal employment



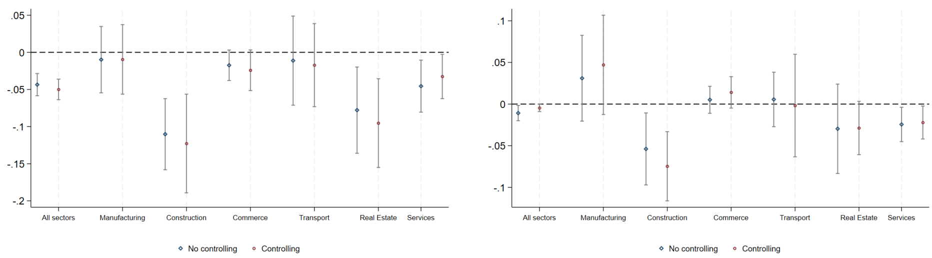
(b) local informal employment



Dependent variables are the logarithm of real hourly wages of informal local workers (Panel A) and the logarithm of the number of informal local workers (Panel B), both measured at the department/sector/year level. Each estimate reports a different regression of the variables, taking out each department. Standard errors clustered at the department level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). All regressions include department and year fixed effects. The regression for the full sample (All sectors) additionally includes sector fixed effects. Control variables include age, education level, 2018 population × year dummies, and the output-input matrix × time-varying GDP by department and sector level. I use national weighted samples from the GEIH.

Figure 1.10: Robustness test: Controlling by department pre-trends

(a) wages of informal employment (b) local informal employment



Dependent variables are the logarithm of real hourly wages of informal local workers (Panel A) and the logarithm of the number of informal local workers (Panel B), both measured at the department/sector/year level. Each estimate reports a different regression of the variables. Standard errors clustered at the department level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). All regressions include department and year fixed effects. The regression for the full sample (All sectors) additionally includes sector fixed effects. Control variables include age, education level, 2018 population × year dummies, and the output-input matrix × time-varying GDP by department and sector level. I use national weighted samples from the GEIH.

Chapter 2

A Lab Experiment on Labor Discrimination Towards Venezuelan Immigrants in Colombia

Mariana Blanco, Darwin Cortés, Nazly López-Peña and Gabriela Triviño

2.1. Introduction

Between 2013 and 2023, Colombia became the primary destination for approximately 7.7 million Venezuelan migrants, with roughly 37.5% of them choosing the country due to its social and geographical proximity (R4V, 2023). This unprecedented inflow created a significant shock to the Colombian labor market, as Venezuelan migrants sought better living conditions in the context of the economic and humanitarian crisis affecting their home country.

In response to this shock, the Colombian labor market has faced a range of challenges. In many cases, factors such as the overqualification of migrants, mismatched skill levels for available job vacancies, the lack of formal recognition of foreign academic certificates, barriers to accessing banking services, irregular migration status, and limited knowledge about formal contracting procedures have discouraged both employers and migrants from participating in the formal labor market, among other issues. These obstacles have persisted despite institutional efforts by the Colombian government to regularize migrants' status and enforce compliance with labor regulations (Bahar et al., 2021; Fundación ANDI, USAID, ACDI-VOCA and Fundación Corona, 2022; García-Suaza et al., 2024; IOM-MPI, 2023; Peñaloza-Pacheco, 2019).

This scenario has raised concerns about social and labor discrimination against Venezuelans in the host countries. There are some anecdotic reports by international organizations suggesting xenophobia and labor discrimination, not only in Colombia but other countries in the Latin America region. Some citizens believe that Venezuelan migrants have come to take their jobs, relate them with criminal networks and violence, believe that are competing with them for scarce resources such as the COVID-19 pandemic, or employers are concerned that hiring Venezuelans could lead them to problematic situations, among others (ACNUR, 2019; OIT, 2020; OIT-BID, 2019). This situation can be particularly problematic, as the social and labor exclusion of immigrants in the host country reinforces existing inequalities and disrupts their path toward well-being, social cohesion, human capital development, and the recognition of their skills and sense of belonging, among other positive outcomes typically associated with labor market access (Agyare, 2020; Ayón and Becerra, 2013; Dietz et al., 2015; Pager et al., 2009).

Venezuelan immigrants in Colombia have reported experiencing both social discrimination and labor exploitation. According to the *Pulso de la Migración* survey conducted by the National Administrative Department of Statistics (DANE for its acronym in spanish), approximately 26.8% of Venezuelan migrants felt discriminated against due to their migratory status, and 33.4% reported discrimination in the workplace. Moreover, among those who encountered barriers when seeking a job, 52.6% attributed these challenges to being asked for documents that they did not have or that were challenging to obtain, 34.5% cited discrimination based on nationality, and 26.2% identified low remuneration or precarious working conditions as significant constraints (DANE, 2023).

Regarding the Employment Service Information System (SISE, for its acronym in Spanish), between 2015 and July 2023, approximately 237,000 Venezuelan immigrants in Colombia applied for a job through the Employability Route[1]. Under this mechanism, institutions and organizations that assist immigrants upon arrival introduce them to the Employability Route and other regularization processes. Simultaneously, the program engages with firms and employers to inform them about the procedures involved in recruiting Venezuelan immigrant workers.

Within this context, our study focuses on the demand side of the labor market, specifically on whether recruiters, who serve as intermediaries between labor supply and demand, are less likely to recommend Venezuelan candidates for job vacancies compared with their Colombian counterparts. Such exclusion may stem from either taste-based discrimination or statistical discrimination, whereby recruiters anticipate that Venezuelan applicants may be less suitable for the position.

For this purpose, we employ the Incentivized Resume Rating (IRR) methodology proposed by Kessler et al. (2019), in which recruiters evaluate a set of real résumés from Colombian and Venezuelan candidates competing for the same job vacancy.

[1] This program provides channels not only to facilitate job placement for immigrants, but also to support employers in their recruitment processes involving Venezuelan candidates (Servicio de Empleo, 2023).

This design seeks to replicate the actual conditions under which recruiters make hiring decisions. Accordingly, we investigate whether the probability of being recommended for a job is systematically associated with the candidate's origin, particularly, whether this probability declines when the applicant is a Venezuelan immigrant. We assess whether recruiters tend to favor Colombian candidates over Venezuelan ones, even when both present similar socio-demographic characteristics and equivalent skill levels.

There is limited empirical evidence on the extent of labor discrimination against Venezuelan immigrants in Colombia or other Latin American countries, particularly through the use of economic or behavioral experiments. The contributions of this research align with those of Bertrand and Mullainathan (2003), Pager et al. (2009), Riach and Rich (1991), among others, who use field experiments to identify labor discrimination against minority groups in developed countries.

In the specific case of discrimination against Venezuelan immigrants in Colombia, this research builds upon studies such as Zanoni and Díaz (2024), who conducted a multi-purpose field experiment with 574 real estate agents and found evidence of discrimination in the housing rental market. The study reported that agents were 24.5 percentage points more likely to choose Colombian families over Venezuelan ones. During the COVID-19 pandemic, Chatruc and Rozo Villarraga (2022) implemented an online survey experiment with Colombian participants and found that natives expressed increased resentment toward migrants during periods of economic crisis. Specifically, respondents in the treatment group held more negative views about the economic contributions of migrants (0.07 standard deviations lower than the control group) and their tax contributions (0.19 standard deviations lower). Notably, these attitudes were reversed when participants were exposed to positive news about the successful development of a COVID-19 vaccine. Additionally, Torres (2021) conducted a correspondence study in Peru with ficticious résumés and found that Venezuelan applicants were 4 percentage points less likely to receive a job callback compared to their Peruvian counterparts. Importantly, this discrimination persisted even when the Venezuelan applicant possessed a valid work permit.

This research contributes to the literature on labor market discrimination against immigrants by employing an experimental design that allows for the direct identification of discriminatory behavior. Unlike studies that rely solely on survey responses, perceptions or fictitious résumés, this study analyzes actual decision-making processes by observing recruiters' behavior when evaluating real résumés. By simulating realistic hiring scenarios, the experimental design captures how recruiters respond to otherwise comparable candidates who differ only in their national origin. This approach enhances external validity and provides robust evidence on whether, and to what extent, nationality influences employment opportunities in practice.

Another contribution is that it not only measures the existence of labor discrimination by observing the decisions of recruiters but also the decisions they made based on their peers. In this sense, we look to identify that labor discrimination against Venezuelan immigrant workers may have several sources, not only because of a prejudice of the subject who has to decide, but also because of the social prejudice that can be isolated from the subject's preferences.

We find evidence of positive labor discrimination in favor of Venezuelan applicants. In the first phase of our experiment, where recruiters make an individual choice, Venezuelan candidates are approximately 60% more likely to be recommended for a job vacancy than their Colombian counterparts. In the second phase, where recruiters were asked to predict their peers' choices, this probability declined to around 39%, yet remained both positive and statistically significant. Our findings suggest that, contrary to widespread perceptions of exclusion, Venezuelan applicants may benefit from favorable bias in certain hiring contexts. Additionally, we find that recruiters tend to prefer candidates who are older and have more work experience. Furthermore, we find that the choice gap is pronounced for in medium-skilled positions and narrows for high-skilled roles

Finally, we assess whether the recruiters' decisions are driven by perceived lower labor performance of Venezuelan candidates rather than by taste-based discrimination against them. Our results show that recruiters were generally able to identify the better performing candidate in mixed nationality pairs, allowing us to reject the hypothesis of taste-based discrimination against Venezuelans.

Besides the introduction, this paper is divided as follows. In section 2, we indicate the design and procedures of our field experiment; in section 3, the hypothesis on which this study is based identifies the existence and type of labor discrimination towards Venezuelan immigrants. Section 4 shows some descriptive statistics, and Section 5 shows the preliminary results of the field experiment and the contrast of the hypothesis. Finally, section 6 concludes with a discussion.

2.2. Experiment Design

Discrimination is an inevitable phenomenon, yet it is often socially undesirable. Consequently, using direct survey questions to detect discriminatory behavior at the individual level is not recommended. When asked about such topics, respondents may provide socially acceptable answers or align with what they believe the interviewer expects, rather than revealing their true preferences. This is known as *social desirability bias* (Fisher and Katz, 2000; Lusk and Norwood, 2009; Norwood and Lusk, 2011; Zerbe and Paulhus, 1987). To minimize this bias and accurately assess whether Venezuelan immigrants are subject to labor market discrimination, and what form this discrimination might take, we designed a behavioral laboratory experiment.

In the literature on labor discrimination, IRRs have been extensively employed to identify hiring biases. These experiments involve presenting pairs of résumés to employers, carefully matched in all relevant qualifications but differing in one specific attribute, such as name, education, age, gender, ethnicity, or work experience. This distinguishing characteristic serves as a signal to the employer, allowing researchers to isolate its effect on hiring decisions (Abubaker and Bagley, 2017; Baert, 2018b; Bertrand and Mullainathan, 2003; Galarza and Yamada, 2014; Kline et al., 2021; Rooth, 2021). Then, we incentivize the reveal of their preferences using a betting system that works as an incentive compatible mechanism. Discrimination is then inferred from systematic differences in callback or selection rates between candidates who are otherwise equivalent.

In our design, we invited two types of participants. On the one hand, we included Colombian nationals and Venezuelan immigrant workers over the age of 18, who constituted the labor supply. They where recruited through social media and in-person outreach at specific locations in Bogotá city, where we knew potential participants would be working. Additionally, the invitation was shared among peers, and many contacted us via WhatsApp to express their interest in participating. A total of 83 individuals took part in the lab sessions between June 27 and August 16, 2023, including 43 Colombians and 54 Venezuelan immigrants.

Participants who expressed interest in the experiment were invited to attend in person at the Rosario Experimental and Behavioral Economics Lab (REBEL), where they were registered in the lab's Online Recruitment System for Economics Experiments (ORSEE). Additionally, some Colombian and Venezuelan participants from the first recruitment phase, who had previously registered in ORSEE through earlier REBEL studies, were also invited to take part in the sessions.

Colombian and Venezuelan workers from the first phase participated in a lab session in which they completed a set of incentivized tasks used as proxies for productivity. These tests assess processing speed and working memory, which are recognized as predictors of job and academic performance as shown in figures B1, B2, B3 and B4 of the Appendix (Kausel et al., 2016; Salgado, 2017; Strittmatter et al., 2020; Vinchur and Koppes, 2011), and have also proven useful for decision-making in personnel selection processes (Murphy, 2002; Schmidt and Hunter, 1998; Schmitt, 2014; Vinchur and Koppes, 2011. The resulting scores allowed us to rank each participant accordingly).

At the end of the session, each participant was asked to complete a survey providing information about their place of birth, age, education level, and the three most recent work experiences with the number of months in each role[2]. We also asked a question regarding their feelings about labor discrimination, as shown in Figure B5 of the Appendix.

[2]For classifying porpuses, we gave four options in the survey: less than 3 months, between 3 months and 6 months, between 7 and 9 months and more than 12 months.

Based on this information, we constructed the labor supply by building a résumé bank that allowed us to match eight pairs of candidates for specific job vacancies, ensuring they shared similar observable characteristics such as age, work experience, and educational attainment.

Table 2.1 presents the résumé pairs selected from our sample. We included four mixed-origin pairs (Venezuelan/Colombian) and four same-origin pairs (either two Colombians or two Venezuelans), which serve as controls. Each pair was matched to a specific job vacancy, chosen according to the required skill level, as detailed in column 7. It is important to note that, for estimation purposes, we created a Labor Experience Index; however, the pairs were presented with the three most recent work experiences for each candidate, including the duration of each position.

The primary differences between candidates within each pair were their place of birth and type of identification document. Additionally, candidates varied in their ranking on the cognitive task, enabling us to define a better performed candidate for each pair. Finally, to ensure comparability in candidate characteristics across pairs, we estimated the mean differences between candidates within each pair. These differences were not statistically significant, confirming that the pairing procedure successfully balanced observable attributes.

Table 2.1: Pairs of selected resumes for recruiters' evaluation in first and second phase

Round	Better Performed	Nationality	Age	Labor Experience Index	Education Level	Job vacancy (*Skill level*)
1	**A**	Colombian	26	44	Technical	Elderly Caregiver
		Venezuelan	32	68	Technical	(*Medium*)
2	**A**	Venezuelan	37	17	Elementary	Storage Inventory Assistant
		Colombian	28	22	Elementary	(*Medium*)
3	**B**	Venezuelan	28	38	College	Route assistant
		Venezuelan	30	46	College	(*Low*)
4	**A**	Colombian	33	56	High-school	Industrial Truck Operator
		Colombian	30	56	High-school	(*Medium*)
5	**A**	Venezuelan	30	41	Technical	Construction assistant
		Venezuelan	33	20	Technical	(*Low*)
6	**A**	Colombian	34	54	Technical	Route coordinator
		Colombian	27	22	Technical	(*Medium*)
7	**B**	Colombian	40	38	Technical	Packaging machine operator
		Venezuelan	35	18	Technical	(*Medium*)
8	**B**	Venezuelan	33	72	College	Musician for events
		Colombian	24	126	College	(*High*)
Mean difference			3.0	-3.5		
(*p-value*)			(0.120)	(0.796)		

Note: This table reports the candidates' information showed to firms and recruiters for making their choices. The Work Experience Index is calculated as a weighted sum of the three most recent job experiences of the participants in the first stage (duration and skill type classified by O*NET), where the most recent job carries the highest weight and the oldest the lowest.

On the other hand, we included recruiters from employment agencies, who are responsible for the routine tasks of receiving, evaluating, and selecting applicants' résumés to recommend them for job vacancies. These recruiters were invited to our stusy through the *National Association of Family Compensation Funds* (ASOCAJAS, for its acronym in Spanish), an organization that maintains direct communication with employment agencies across the country.

Recruiters were invited to participate in an in-person lab session at REBEL. At the beginning of the session, each recruiter was asked to complete one of the four cognitive tasks previously performed by the candidates in the first stage. The specific task assigned (Coding Words) was selected due to its predictive power over performance in the remaining tasks (see Table 2.11 in the Appendix). This step aimed to familiarize recruiters with the nature and difficulty of the tasks undertaken by both Venezuelan and Colombian participants, while minimizing cognitive fatigue. Upon completing the task, each recruiter received a monetary endowment equivalent to 250 tokens[3].

Consequently, each recruiter was presented with the previously mentioned eight pairs of résumés we build, as illustrated in the example in Figure 2.A.1 in the Appendix. Before making any decisions, recruiters were informed that all candidates had completed the same cognitive task they had just undertaken, and that performance on this task would serve as a proxy for productivity. Accordingly, the candidate with the better task performance is assumed to be more productive. However, recruiters were not provided with the candidates' actual test scores or ranking within each pair.

For the mixed-origin pairs (1, 2, 7, and 8 of Table 2.1), we alternated the on-screen placement of candidates by nationality, so that each appeared in both the left-hand position (Position A) and the right-hand position (Position B). In addition, each of the eight résumé pairs was displayed in random order; for instance, the first pair shown to a recruiter could correspond to pair number 6, followed by pair number 4, and so on, until all eight rounds were completed.

One limitation of our experimental design concerns the composition of our candidates' pool, which predominantly includes individuals with low to medium skill levels, according to the O*NET Job Zones classification. Consequently, we were unable to construct résumé pairs suitable for white-collar positions. Nevertheless, this limitation reflects the labor market realities faced by Venezuelan migrants in Colombia. According to Bahar et al. (2021), Bonilla-Mejía et al. (2020), and DANE (2021), between 80% and 90% of Venezuelan immigrants are employed in the informal sector, primarily in low- to medium-skilled occupations.

For each résumé pair, in the first phase of recruiters exercise, they were presented with the following question: *"Candidate A and Candidate B are applying for a job vacancy as (job vacancy). Who do you believe performed better on the cognitive task and is therefore expected to have a better work performance?"* In this context, recruiters had to base their decisions solely on the résumé information and their own beliefs regarding each candidate performance, across all eight evaluation rounds.

[3]Each 10 tokens equals to COP $2,000

Next, in the second phase, recruiters were asked to predict the behavior of their peers participating in the same session. They were shown the same eight pairs of résumés appying for the same role, but responded to a slightly modified question: *Candidate A and Candidate B are applying for a job vacancy as (job vacancy). Who do you think was most frequently selected by the participants in this room during the previous stage?*.

In each selection round of the two phases, recruiters used a betting mechanism designed to incentivize the revelation of their true preferences. At the beginning of the session, they received a monetary endowment converted into tokens, which they could allocate to the candidate they believed was better suited for the job. Recruiters were instructed that they could bet any amount between 0 and 100 tokens for each round of résumés in the first phase and 50 tokens for each round of résumés in the second phase. If the candidate they bet on was objectively the better performer, they would receive a monetary gain; otherwise, they would incur a loss.

With this in mind, participants were informed that gains and losses would accumulate across rounds, and that the 250 tokens earned for completing the Coding Words task at the beginning would be used to offset potential losses or increase total gains. The were also awarded that four out of the eight rounds would be randomly selected for actual payment at the end of the session. Additionally, if total losses exceeded accumulated gains, including the 250 initial tokens, participants had to leave the session with no earnings. This incentive compatible design ensured that recruiters had a financial stake in accurately identifying the most productive candidate, thereby motivating them to reveal their true beliefs (Azrieli et al., 2018; Danz et al., 2024; Toulis et al., 2015; Voslinsky and Azar, 2021).

This approach aligns with the Incentivized Resume Rating (IRR) methodology proposed by Kessler et al., 2019, which demonstrates that combining real résumés with incentive compatible mechanisms produces more accurate and policy relevant insights into employer preferences. By using authentic candidate profiles rather than fictitious ones, we aim to prevent potential skepticism from recruiters regarding the credibility of the résumés, which could otherwise compromise the realism of the task and weaken the external validity of our findings. This design choice allows for a more faithful representation of actual labor market dynamics and enhances the robustness and generalizability of our experimental results.

At the end of the exercise, recruiters were asked to complete a questionnaire collecting socio-demographic information, including age, gender, and education level. Additionally, we included a set of seven validated hypothetical scenarios to assess individual risk preferences, following the methodology proposed by Dohmen et al., 2011. This allows us to explore whether risk aversion may act as a potential determinant of discriminatory behavior in the labor market (Baert, 2018a; Lippens et al., 2021; Zhan and Deole, 2022).

To obtain a consistent and valid measure of risk propensity, we constructed an index using a Confirmatory Factor Analysis (CFA)[4], which is subsequently used in regression analyses to assess whether risk attitudes systematically correlate with discriminatory patterns in recruiters' decision-making.

To complement this analysis, we also examine discriminatory beliefs by incorporating into the questionnaire a set of adapted items from the Latinobarómetro survey. These items were selected to capture attitudinal dimensions particularly relevant to our context. As with the risk preference measure, we also constructed a summary index using CFA to capture latent discriminatory predispositions[5].

2.3. Hypothesis

We formulate three hypotheses concerning recruiters' decision-making behavior in the context of candidates evaluation. Relying on performance in cognitive tasks as a proxy for labor productivity, and considering the résumé information available to recruiters, we expect to observe systematic patterns in candidate selection if discriminatory behavior is present.

[4] Lower index values indicate higher risk aversion, while higher values reflect a greater willingness to take risks.

[5] Lower index values indicate weaker discriminatory tendencies, while higher values reflect stronger discriminatory attitudes.

Hypothesis 1: A Venezuelan candidate has a lower probability of being recommended by a recruiter for a job vacancy compared to his Colombian counterpart.

As mentioned, to elicit recruiters' genuine decision-making criteria, rather than socially desirable responses, we implemented an incentive-compatible design based on Induced Value Theory (Smith, 1976). According to this theory, revealing true preferences requires a carefully structured reward system in which the incentives are strong enough to outweigh alternative motivations, thereby inducing participants to act in alignment with their actual preferences and beliefs (Dixit et al., 2017; Goodie, 2003; Kausel et al., 2016).

The monetary earnings of recruiters in the experimental exercise could increase, decrease, or remain unchanged depending on the accuracy of their decisions. Based on résumé information and the expected productivity associated with the cognitive tasks, recruiters were expected to infer which candidate likely performed better and to place their bets accordingly, independently of the candidate's nationality. If recruiters follow this logic, they will correctly predict performance, win the bet, and increase their utility. However, if recruiters systematically attribute lower expected performance to Venezuelan candidates compared to Colombians, even when résumés are comparable, this constitutes evidence of systematic discriminatory behavior. We define this pattern of bias as *Primary Bias*.

Hypothesis 2: In the absence of discrimination, recruiters may still expect their peers to discriminate towards Venezuelan candidates. That is, they believe other recruiters are more likely to recommend Colombian candidates over equally qualified Venezuelan ones.

Even in the absence of a Primary Bias on the part of recruiters, a bias with similar consequences may still arise due to their perceptions about the preferences of their peers. Specifically, if a recruiter predicts candidates' performance independently of nationality, but assumes that others systematically expect lower performance from Venezuelan applicants, and therefore bets on the Colombian candidate for the job vacancy, this constitutes discriminatory behavior driven by perceived social norms (Bicchieri, 2005; Charness et al., 2025; Rokeach and Mezei, 1966). We refer to this behavioral mechanism as *Secondary Bias*.

Hypothesis 3: Any observed labor discrimination against Venezuelan immigrants is attributable to recruiters' perceptions of lower expected performance, rather than to taste-based discrimination.

Beyond identifying the presence of labor discrimination, we aim to distinguish between its underlying mechanisms. The literature typically differentiates between two broad types of discrimination, namely, statistical and taste-based. Statistical discrimination occurs when employers rely on average group characteristics to infer individual productivity (Arrow, [1973, 1998]; Schwab, 1986; Tomasovic-Devey and Skaggs, 1999). In our context, this form of discrimination is reflected in recruiters' expectations about the performance of Venezuelan immigrant candidates.

However, even when a group is known to exhibit performance levels comparable to others, employers may still display a subjective or irrational aversion toward that group, a phenomenon known as taste-based discrimination. In our context, if a recruiter is repeatedly presented with pairs consisting of a Colombian and a Venezuelan candidate with similar résumés, and systematically fails to select the Venezuelan candidate despite superior cognitive task performance, this would constitute evidence of taste-based discrimination against Venezuelan immigrants (Becker, 2010; Bohren et al., 2019; Rubinstein and Brenner, 2013). Conversely, if recruiters consistently make accurate predictions based on résumé information and actual performance, we can rule out the presence of taste-based discrimination and instead attribute observed disparities to statistical discrimination.

2.4. Descriptive Statistics

Our objective is to closely replicate the real conditions faced by Venezuelan immigrants in the Colombian labor market, as well as the decision-making environment encountered by recruiters and employers. Unlike traditional Correspondence Testing Experiments (CTEs), which often rely on stylized or hypothetical profiles, our labor supply sample is built using real individuals with documented work histories and objectively measured performance outcomes.

We present descriptive statistics for the 83 participants who took part in the first stage of our experimental sessions. As shown in Table 2.2, Venezuelan immigrants and Colombian nationals in our sample exhibit highly similar observable characteristics. Although some variation exists in individual attributes such as age, work experience, or education level, we find no statistically significant differences between the two groups. On average, participants are approximately 30 years old and report comparable levels of education, typically ranging from secondary school to technical training[6]. While Colombian participants show a slightly higher average score on the Labor Experience Index, this difference is not statistically significant[7]. This high degree of comparability across key dimensions strengthens the internal validity of our experimental design, as it confirms that the matched pairs are based on similar profiles and enables us to isolate the effect of nationality in recruiters' decision-making.

Table 2.2: Descriptive statistics of Venezuelan immigrant workers vs. Colombian workers

	All sample	**Colombians**	**Venezuelans**	**Difference** (*p-value*)
Age	29.7	29.3	30	-0.667
	(0.55)	(0.75)	(0.78)	(0.559)
Labor experience Index	42.7	44.0	41.9	2.100
	(2.05)	(3.51)	(2.52)	(0.620)
Education level	2.6	2.6	2.6	-0.024
	0.10	(0.13)	(0.13)	(0.902)
Observations	83	33	50	

Table reports means and standard deviations in parentheses. Last column reports mean differences of variables between Colombians and Venezuelans (diff mean(Colombians) - mean (Venezuelans)) and *p-value* in parentheses (*** p<0.01, ** p<0.05, *p<0.1).

Table 2.3 provides additional detail on participants' education levels and the skill requirements of their most recent occupations. The majority of participants have attained an education level between high school and technical training, with a smaller share holding college degrees. Only one individual reported having no

[6] Participants were asked to select one of the following education levels: 1 = Elementary, 2 = High School, 3 = Technical, 4 = College.

[7] The Labor Experience Index is a weighted sum based on participants' three most recent jobs, incorporating both job duration and skill type, following the O*NET Job Zones classification O*NET, 2025. More recent jobs receive greater weight, while earlier jobs are weighted less.

formal education. While a larger proportion of Colombians in the sample hold either a high school or technical degree, college education is slightly more prevalent among Venezuelan participants.

Regarding occupational skill levels, most participants have experience in jobs requiring low to medium labor skills, based on the O*NET Job Zones classification. Notably, a higher proportion of Venezuelan participants have experience in low-to-medium skill occupations compared to their Colombian counterparts.

Table 2.3: Share of Colombians and Venezuelans by Education level and labor skills (%)

	All sample	**Colombians**	**Venezuelans**
Education level			
Elementary	6.3	4.8	7.4
High school	4.9	50.0	46.3
Technical	29.2	31.0	27.8
College	15.6	14.3	16.7
None	1.0	0.0	1.9
Skills level (Labor experience)			
Low	15.7	21.2	12.0
Low-Medium	65.1	48.5	76.0
Medium	9.6	24.2	8.0
High-Medium	9.6	6.1	4.0
High-Medium	0.0	0.0	0.0
Observations	83	33	50

This table reports the variable proportions by nationality for the whole sample. The required skills level for job occupations is defined according to the Job Zones of the Occupational Information Network (O*NET, 2025).

On the other hand, Table 2.4 presents key socio-demographic characteristics of the recruiters. The sample consists of a relatively young and highly educated group, with a high proportion of female participants. On average, participants are 34 years old, with little variation across gender. Education levels range from undergraduate to graduate studies, with average scores of 3.29 for women and 3.27 for men on a four-point scale[8]. Regarding behavioral indicators, female participants tend to exhibit greater risk aversion, while male participants are more likely to be

[8]Participants were asked to select one of the following education levels: 1 = High School, 2 = Technical, 3 = Undergraduate, 4 = Graduate.

risk-seeking. In terms of the Discrimination Index, both groups scored close to zero, indicating no evident discriminatory attitudes at this preliminary stage.

Table 2.4: Socio-demograpics of recruiters

	Women			**Men**		
	Mean	**SD**	**N**	**Mean**	**SD**	**N**
Age	34.42	5.03	66	34.18	5.58	11
Education level	3.29	0.46	66	3.27	0.48	11
Risk Index	-0.03	1.20	66	0.16	0.52	11
Dsicrimination Index	0.00	0.4	66	-0.03	0.29	11

This table reports the recruiters' socio-demographic information collected at the end of each lab session. Participants were asked to select one of the following education levels: 1=High school, 2=Technical, 3=Undergraduate, 4=Graduate. The Risk Index was constructed using Confirmatory Factor Analysis (CFA) applied to responses from seven hypothetical scenarios in which participants selected an option on a scale from 1 (completely risk-averse) to 10 (completely risk-seeking). The Discrimination Index was also derived using CFA, based on a set of attitudinal questions adapted from the Latinobarómetro survey.

2.5. Results

We now present the main findings of our study, organized around the three central hypotheses. The analysis is based on the decisions made by 77 recruiters from employment agencies. Each recruiter completed two decision-making phases, with each phase consisting of eight rounds of candidate pair evaluations. This resulted in a total of 16 decisions per recruiter and 308 total choices per phase, followed by a final questionnaire, as previously described. In the first phase, participants made individual recommendations, while in the second phase, they were asked to predict the selections made by their peers within the same lab session.

Panel A of Table 2.5 shows that, overall, recruiters were more likely to recommend Candidate B over Candidate A in the individual decision phase. The selection gap was notably wider and statistically significant in homogeneous nationality pairs (Colombian/Colombian or Venezuelan/Venezuelan). For heterogeneous pairs (Colombian/Venezuelan), although the difference was still statistically significant, it was smaller in magnitude. Next, in Panel B of the second phase, where recruiters were asked to predict their peers' choices, responses became more conservative. For heterogeneous pairs, selection differences disappeared, reaching an almost 1:1 selection ratio.

Table 2.5: Mean difference in selection of pairs of resumes by recruiters

	A	**B**	**Ratio**	**Difference** *(p-value)*
Panel A: First phase - Individual choice				
All sample	38.2%	61.9%	0.62	-23.7%
	[616]	[616]		(0.000)
Homogeneous pairs	32.5%	67.5%	0.48	-35.1%
	[308]	[308]		(0.000)
Mixed pairs	43.8%	56.2%	0.78	-12.3%
	[308]	[308]		(0.002)
Panel B: Second phase - Peers' choice prediction				
All sample	41.2%	58.8%	0.70	-17.5%
	[616]	[616]		(0.000)
Homogeneous pairs	33.8%	66.2%	0.51	-32.5%
	[308]	[308]		(0.000)
Mixed pairs	48.7%	51.3%	0.95	-3.6%
	[308]	[308]		(0.520)

The table presents the selection rates for candidates A and B. The numbers in brackets indicate the total number of resumes evaluated by recruiters. Column 4 reports the ratio of selections between candidate A and candidate B. Column 5 displays the difference in selection rates within each type of pair, along with the p-value that assesses the null hypothesis that the selection rates are equal.

The previous results provide an initial approximation. However, in mixed-nationality pairs, the assignment of nationality varies between candidates; that is, either Candidate A or Candidate B may be Colombian or Venezuelan, depending on the round. Table 2.6 presents the average differences in selection rates within these mixed pairs. The results reveal a clear and statistically significant preference among recruiters for recommending Venezuelan candidates over their Colombian counterparts. Furthermore, recruiters' predictions about their peers' choices closely mirror their own individual decisions from the first phase, albeit in a slightly more conservative direction.

Table 2.6: Mean difference in selection of pairs of resumes by recruiters by nationality

	Colombians	**Venezuelans**	**Ratio**	**Difference** *(p-value)*
Individual choice	25.6%	74.4%	0.34	-48.7%
	[308]	[308]		(0.000)
Peers' choice prediction	31.2%	68.8%	0.42	-37.7%
	[308]	[308]		(0.000)

Note: The table presents the selection rates for candidates of mixed nationality. The numbers in brackets indicate the total number of resumes evaluated by recruiters. Column 4 reports the ratio of selections between nationalities. Column 5 displays the difference in selection rates, along with the p-value that assesses the null hypothesis that the selection rates are equal.

Recruiters made their decisions not only based on candidates' nationality, but also considering other observable characteristics such as age, work experience, and the specific job position to which each pair of candidates applied. To assess whether nationality had an independent effect on the probability of being recommended for a job, it is necessary to control for these attributes and distinguish between different comparison contexts.

Specifically, in this experimental design, the treatment arises from the type of candidate pairs that recruiters evaluated, either homogeneous nationality or mixed. Discrimination based on nationality could only plausibly occur in the heterogeneous setting where résumés explicitly differed by national origin. To formally capture this contextual heterogeneity, we estimated an interacted probit model that allowed the effect of nationality to vary by pair type, while controlling for observable résumé characteristics that varied slightly within pairs, such as age and work experience[9].

Result 1: Venezuelan candidates had a significantly higher probability of being recommended by recruiters compared to their Colombian counterparts.

Table 2.7 presents the marginal effects of résumé characteristics on the probability of being selected across different phases. We discarded a few observations in which recruiters chose to bet 0 tokens on either candidate, indicating that the

[9] Although education level was included in the résumés presented to recruiters, it was held constant within each candidate pair by design. This allows us to isolate the effect of nationality, net of education, under the assumption that recruiters considered both candidates to be equally qualified in this dimension.

decision was not made. Column 1 reports recruiters' individual choices and, as expected, nationality was not informative in homogeneous pairs. However, in mixed pairs, where national origin varied between candidates, Venezuelan applicants were 53% more likely to be recommended than their Colombian counterparts. When additionally controlling for the job vacancy associated with each round, this probability increased to 60% (Column 2).

In addition, for mixed pairs, work experience and age were positively valued; that is, recruiters tended to recommend candidates who were older and more experienced. In contrast, for homogeneous pairs, work experience was not a significant predictor of recommendation, and the pattern reversed for age; younger candidates were approximately 3% more likely to be selected.

Result 2: In the presence of positive discrimination favoring Venezuelan candidates, recruiters predict a similar behavior among their peers. Consequently, we find no evidence of *Secondary Bias*.

Consequently, when recruiters were asked to predict the choices of their peers (Columns 3 and 4) within the same session, the estimated likelihoods were more conservative, although the overall patterns remained consistent. In mixed pairs, recruiters expected their peers to exhibit a preference for Venezuelan candidates, who were 42% more likely to be recommended compared to their Colombian counterparts. This estimated gap remained robust, at approximately 39%, even after accounting for variation across job vacancies. Regarding labor experience and age, the observed patterns were broadly similar to those in the individual decision phase. These results suggest that recruiters had a reasonably accurate perception of how the market responds to migrant participation.

Table 2.7: Marginal Effects of resume characteristics evaluated by recruiters on the probability of being recommended for a job position

	Individual choice		**Peers' choice prediction**	
	(1)	(2)	(3)	(4)
Nationality	-0.067	0.022	-0.064	0.034
[Venezuelan=1]	(0.058)	(0.095)	(0.062)	(0.103)
Nationality×Treatment	0.532***	0.603***	0.419***	0.387***
[Venezuelan=1]	(0.072)	(0.105)	(0.084)	(0.113)
Work Experience	-0.002	-0.001	-0.002	-0.0002
	(0.003)	(0.004)	(0.003)	(0.004)
Work Experience×Treatment	0.007**	0.016***	0.005	0.009*
	(0.003)	(0.003)	(0.005)	(0.005)
Age	-0.034***	-0.035***	-0.035***	-0.039***
	(0.010)	(0.010)	(0.010)	(0.011)
Age×Treatment	0.051***	0.046***	0.049***	0.051***
	(0.012)	(0.014)	(0.012)	(0.015)
Job vacancy controls	No	Yes	No	Yes
Observations	1,222	1,222	1,220	1,220

The dependent variable is a dummy that equals to 1 if the candidate in the pair was selected in a given round, and 0 otherwise. Standard errors in parentheses are clustered at the recruiter level (*** $p<0.01$, ** $p<0.05$, *$p<0.1$). Each column corresponds to a separate model estimation. All regressions include job vacancy fixed effects. Homogeneous pairs refer to candidate pairs with the same nationality (Colombian/Colombian or Venezuelan/Venezuelan). Mixed pairs refer to candidates with different nationalities.

Table 2.8 shows substantial differences in candidate selection across job vacancies when comparing mixed-nationality pairs, with the exception of the *Musician for Events* position, where the difference was not statistically significant in either the individual choice or the peers' choice prediction. Interestingly, the selection gaps in peer predictions were generally narrower than those observed in individual decisions. These results raise the question of whether the observed nationality effects remain significant after controlling for candidates' observable characteristics. To address this, we conducted a likelihood-ratio test to assess the joint significance of nationality within a multivariate framework. The results confirm that these patterns persist even after accounting for other résumé characteristics (χ^2 = 146.4, p-value = 0.000

for individual choices; $\chi^2 = 50.8$, p-value = 0.000 for peer choice predictions), underscoring the robust role of nationality in the selection process.

Table 2.8: Candidates' election by job vacancy in the mixed nationality pairs

Job vacancy	**Election rate**		**Difference**
	Colombians	**Venezuelans**	*(p-value)*
	Panel A: Individual choice		
Elderly Caregiver	5.2%	94.2%	-89.6%
			(0.000)
Storage Inventory Assistant	7.8%	92.2%	-84.4%
			(0.000)
Packaging machine operator	34.2%	64.8%	-31.6%
			(0.000)
Musician for events	55.8%	44.2%	1.7%
			(0.149)
	Panel B: Peers' choice prediction		
Elderly Caregiver	19.5%	80.5%	-61.0%
			(0.000)
Storage Inventory Assistant	16.9%	83.1%	-66.2%
			(0.000)
Packaging machine operator	39.5%	60.5%	-21.1%
			(0.009)
Musician for events	48.1%	51.9%	-3.9%
			(0.631)

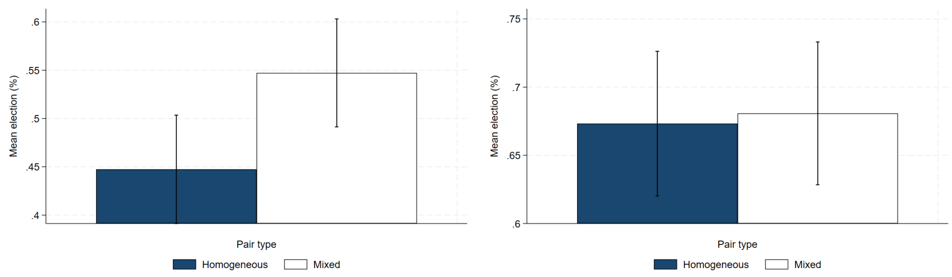
The likelihood-ratio test was conducted using the `lrtest` Atata command on stored estimates from two probit regressions. The unrestricted model included a dummy for candidate nationality, four job vacancy dummies, and the interaction terms between nationality and each job vacancy. The restricted model included only the nationality dummy and the job vacancy dummies. Standard errors were clustered at the recruiter level. (*** p<0.01, ** p<0.05, * p<0.1).

Result 3: We find no evidence that recruiters systematically assigned lower expected performance to Venezuelan candidates when résumés were comparable in observable characteristics to their Colombian counterparts. Therefore, we rule out the presence of *Primary Bias*.

An additional concern relates to the accuracy of recruiters' predictions. Figure 2.1a shows that recruiters correctly identified the better-performing candidate in approximately 45% of the individual decisions, with accuracy increasing to around 55% in the case of mixed pairs. When predicting their peers' choices, Figure 2.1b displays a notable improvement in predictive accuracy, recruiters correctly anticipated the most frequently selected candidate in about 67% of the cases, regardless of the pair type.

Figure 2.1: Recruiters' prediction for mixed pairs

(a) Individual choice (b) Peers' choice prediction

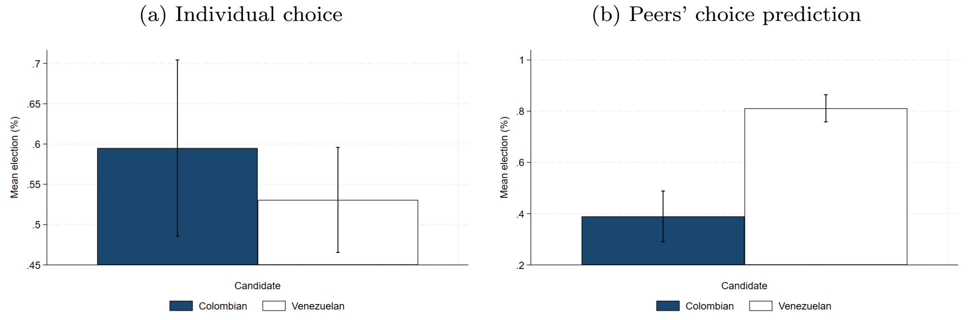


Figures display mean prediction accuracy by pair type (homogeneous vs. mixed nationality). Panel (a) corresponds to individual choices made in the first phase (N = 168), and Panel (b) to predictions of peers' choices in the second phase (N = 139). In both cases, observations in which recruiters placed 0 tokens were excluded. Error bars represent 95% confidence intervals.

To further explore these dynamics in mixed-nationality pairs, we examine whether recruiters' predictions aligne with candidates' actual performance outcomes. Figure 2.2a shows that, in the individual decision phase, recruiters are slightly more accurate in predicting the performance of Colombian candidates (about 59%) than that of Venezuelan candidates (about 53%), although this difference is not statistically significant.

Figure 2.2b reveals that recruiters predict their peers' choices more accurately when the selected candidate is Venezuelan, with an accuracy rate close to 80%, compared to only about 40% when the selected candidate is Colombian. Taken together, these results suggest that while recruiters are moderately accurate in assessing individual candidate performance, their expectations about peer behavior reveal a strong belief that Venezuelan candidates are more likely to be selected.

Figure 2.2: Recruiters' prediction for mixed pairs



Figures display mean prediction accuracy by nationality in the mixed pairs. Panel (a) corresponds to individual choices made in the first phase ($N = 204$), and Panel (b) to predictions of peers' choices in the second phase ($N = 209$). In both cases, observations in which recruiters placed 0 tokens were excluded. Error bars represent 95% confidence intervals.

We also seek to rule out the possibility that candidate selection is influenced by recruiters' social beliefs about discrimination and risk-taking behavior. We investigate whether individual risk preferences can serve as a potential determinant of discriminatory behavior in the labor market (Baert, 2018a; Lippens et al., 2021; Zhan and Deole, 2022), and whether potential discriminatory behavior may be influencing recruiters' choices. Panel B of Table 2.9 presents the estimates from a conditional logit choice model, indicating that neither individual risk preferences nor measured discriminatory attitudes significantly influence recruiters' decisions. Panel A presents the characteristics that vary across rounds and inform the recruiters' decisions, by nationality. Based on these results, we observe that candidate selection is not driven by individual ideological or behavioral predispositions.

Table 2.9: Odds ratio for choice decisions in mixed nationality candidates

	Base alternative candidate: Colombian	
	Individual choice	Peers' choice prediction
	(1)	(2)
Panel A - Candidates characteristics		
Work Experience	1.042***	1.022***
	(0.006)	(0.004)
Age	1.035	1.033
	(0.026)	(0.023)
Panel B - Recruiters' characteristics		
Discrimination Index	1.092	0.926
	(0.491)	(0.366)
Risk Index	0.901	0.918
	(0.152)	(0.182)
Observations	616	616
Choice cases observations	308	308

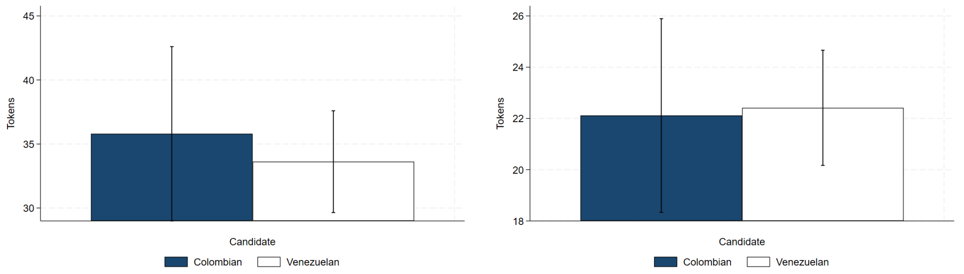
The dependent variable is a dummy equal to 1 if the candidate in the pair was selected in a given round, and 0 otherwise. Each recruiter evaluates two alternatives per round: one Colombian and one Venezuelan candidate. The panel structure takes the recruiter as the observational unit and the rounds as the time dimension. Reported estimates are odds ratios from conditional logit models. An odds ratio greater than 1 indicates a positive association between the predictor and the likelihood of candidate selection, i.e., when recruiters value work experience or age, when exhibit greater discrimination, or are more risk-seekers. Standard errors are clustered at the recruiter level. (*** p<0.01, ** p<0.05, * p<0.1). Each column represents a separate model estimation.

Result 4: There is no evidence that recruiters assign lower bets to Venezuelan candidates when résumés are comparable with their Colombian counterparts in observable characteristics within mixed-nationality pairs.

Our results further show that the amount of tokens recruiters bet on their chosen candidate does not differ by nationality in the mixed pairs, suggesting that betting behavior is not influenced by the candidate's origin and that recruiters trust their own judgment. Figure 2.3a depicts that, in the individual choice phase, bets placed on selected Colombian candidates average 36 out of 100 tokens, while those on Venezuelan candidates average 34 out of 100 tokens. However, this difference is not statistically significant. Interestingly, when recruiters predict their peers' decisions, they allocate similar amounts to both Venezuelan and Colombian candidates, (approximately 22 out of 50 tokens).

Figure 2.3: Recruiters' bets for mixed pairs

(a) Individual choice (b) Peers' choice prediction



Figures show the mean of bet tokens on the selected candidate in the mixed pairs. N = 308 for both first and second phases. In both cases, observations in which recruiters placed zero tokens were excluded. Error bars represent 95% confidence intervals.

In addition, Table 2.10 shows that, in the individual choice phase, the amount bet on the selected candidate is positively associated with work experience and, to a lesser extent, with education, particularly when round and recruiter fixed effects are included (Column 2). However, this pattern changes in the peers' choice prediction phase. Once fixed effects and previous earnings are accounted for (Column 6), the strongest predictor of betting behavior becomes candidate nationality. Recruiters bet approximately 0.22 to 0.27 standard deviations more when the candidate is Venezuelan, suggesting the presence of a social norm effect.

Table 2.10: Resume characteristics and bets on the selected candidate of the mixed nationality pairs

	Individual choice		**Peers' choice prediction**			
	(1)	(2)	(3)	(4)	(5)	(6)
Nationality	0.137	0.189	0.128	0.225***	0.270**	0.220***
[Venezuelan=1]	(0.130)	(0.125)	(0.139)	(0.083)	(0.123)	(0.082)
Work Experience	0.007***	0.008**	0.005**	-0.001	0.005**	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Age	0.017	0.015	0.008	-0.015	0.017	-0.014
	(0.022)	(0.014)	(0.018)	(0.011)	(0.016)	(0.012)
Education	0.143**	0.103	0.076	0.264	-0.022	0.231***
[Above high-school=1]	(0.072)	(0.104)	(0.087)	(0.085)	(0.077)	(0.079)
Previous toks (SD)					0.019***	0.003
					(0.002)	(0.003)
Mean Dep Var	34.2	34.2	22.3	22.3	22.3	22.3
Fixed Effects	No	Yes	No	Yes	No	Yes
R-squared	0.029	0.860	0.022	0.830	0.343	0.831
Observations	308	308	308	308	308	308

The dependent variable is the standard deviation of the number of tokens bet on the selected candidate within mixed-nationality pairs. Standard errors in parentheses are clustered at the recruiter level (*** p<0.01, ** p<0.05, *p<0.1). Each column corresponds to a separate model estimation. Columns 2, 4 and 6 include round and recruiter fixed effects.

2.6. Discussion and conclusions

This study aims to identify the extent and nature of labor discrimination towards Venezuelan immigrants in Colombia. To achieve this, we designed and implemented a CTE that incorporates an incentivized betting mechanism, following the IRR methodology proposed by Kessler et al. (2019). This experimental framework allows us to elicit recruiters' preferences under a job selection process involving real résumés from both Venezuelan and Colombian candidates, thereby closely replicating real-world hiring conditions while controlling for observable characteristics. Our main findings show that Venezuelan candidates are more likely to be recommended for a job vacancy that their Colombian counterparts.

A deeper analysis reveals that recruiters tend to favor Venezuelan and older candidates, when compete with Colombians. However, this pattern reverses when recruiters evaluate pairs of candidates with the same nationality. In homogeneous comparisons, recruiters are more likely to recommend candidates who are both younger and more experienced.

One possible explanation for this asymmetry is that, in mixed nationality pairs, recruiters may apply compensatory criteria rooted in perceived social inclusion norms, leading them to favor Venezuelan immigrants. This tendency becomes particularly evident in the second phase of the experiment, where recruiters predicted their peers' choices. In that context, Venezuelan candidates were not only more likely to be recommended but also received higher average bets compared to the individual choice phase. Moreover, recruiters correctly anticipated their peers' behavior in approximately 80% of the cases. In contrast, for the homogeneous nationality pairs, traditional productivity signals such as age and experience regain prominence in hiring decisions.

Another important finding concerns recruiters' personal attitudes. First, the evidence shows no systematic tendency toward discriminatory beliefs, and participants who are predominantly women, exhibit risk-averse profiles. Second, neither risk preferences nor discriminatory attitudes significantly predict recruiters' choices. In the context of mixed nationality comparisons, there is no clear evidence of labor discrimination driven by individual taste or prejudice.

This finding is further supported by results from the phase in which recruiters were asked to identify the candidate they believed performed better on the task designed to predict labor productivity, and based on that would recommended him for a job vacancy. In this context, recruiters correctly identified the better performing candidate in approximately 55% of the cases. Based on these results, we conclude that recruiters' decisions are partially driven by résumé information, particularly by demographic characteristics that appear to influence their selections, and by their beliefs about candidates' performance in the productivity tasks.

Additionally, we examine whether selection patterns vary by job vacancy. We find that Venezuelan candidates are significantly more likely to be preferred for medium skilled roles. However, for positions classified as high-medium skilled, this pattern does not persist, and the difference in selection by nationality is no longer statistically significant. Although relevant, this result is partly shaped by the types of roles to which candidates applied, and it also reflects a limitation of our design. The résumé bank constructed during fieldwork did not allow for the matching of candidate pairs applying to high-skilled or white-collar positions, due to the occupational profiles of the participants recruited in the first stage of the experiment. This constraint may limit the generalizability of our findings and presents a valuable direction for future research.

2.A Appendix

2.A.1. Resumes

Figure A1: Types of Resume Pairs Evaluated by Firms and Recruiters

Dupla 7

El Candidato A y el Candidato B se están presentando para un puesto vacante de **operario de máquina de empaquetado**?. ¿**Quién cree que está mejor posicionado en el ranking de desempeño** y, por tanto, se espera de él un mejor rendimiento laboral?

Tipo de documento	Cédula de Ciudadanía
Número de documento	80.746.XXX
Lugar de nacimiento	Bogotá D.C.
Edad	40
Experiencia laboral	• Jardinero de zonas verdes - Más de 12 meses • Guarnecedor de calzado - Entre 7 y 9 meses • Bodeguero - Entre 3 y 6 meses
Nivel educativo	Técnico

○ Candidato A

Tipo de documento	Permiso de Protección Especial
Número de documento:	7.004.XXX
Lugar de nacimiento	Los Puertos (Venezuela)
Edad	35
Experiencia laboral	• Oficios Varios - Más de 12 meses • Maquinista - 3 meses • Trabajador fábrica de escritorios - Entre 3 y 6 meses
Nivel educativo	Técnico

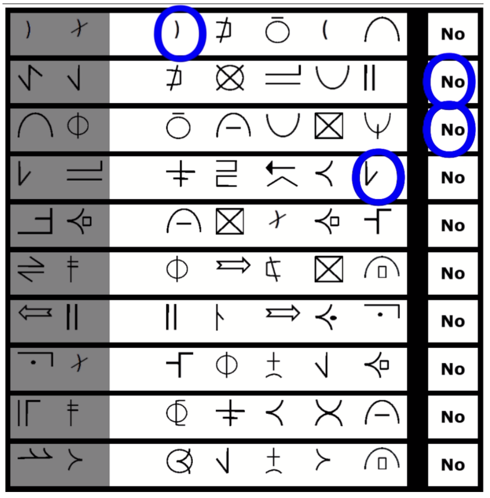
○ Candidato B

De los **100** tokens que tiene a su disposición ¿Cuántos apostaría por el candidato escogido?

Tokens

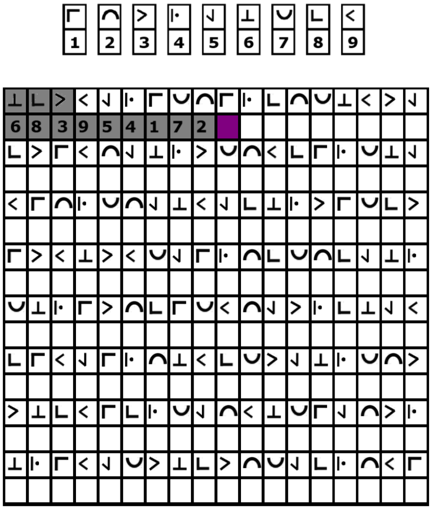
2.A.2. Cognitive skills tasks

Figure B1: Symbol Search Task (Processing speed)



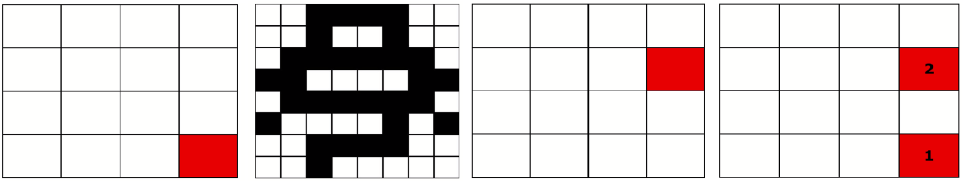
Taken from Finn et al., 2014

Figure B2: Symbol Substitution (Processing speed)



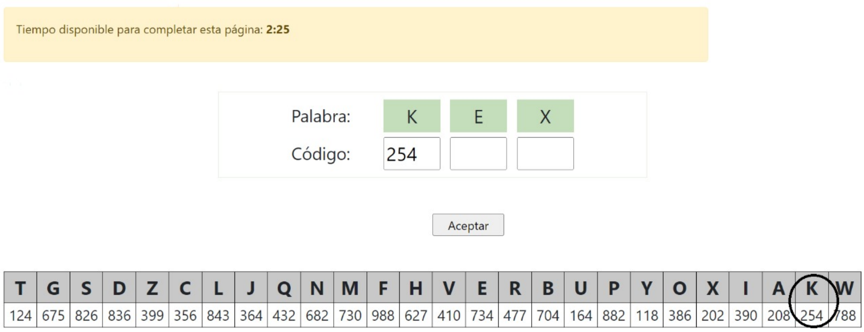
Taken from Finn et al., 2014

Figure B3: Symmetry span (Working memory)



Taken from Finn et al., 2014

Figure B4: Coding Words (Working memory)



Taken from Finn et al., 2014

Figure B5: Survey questions about labor discrimination feelings

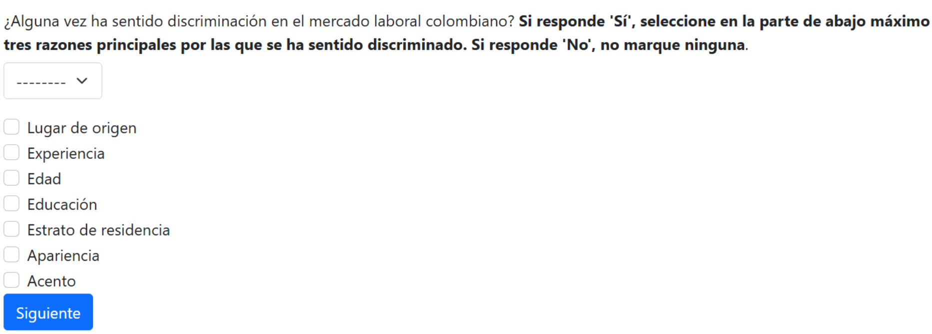


Table 2.11: Coding Words Performance as a Predictor of Symbol Search, Symmetry Span and Symbol Substitution tasks Performance.

	Symbol Search	Symmetry Span	Symbol Substitution
Coding Words	1.215***	0.846***	2.065***
	(0.289)	(0.299)	(0.406)
R^2	0.18	0.10	0.24
Observations	83	83	83

Variables are represented in accumulated points gained by the participants at the end of each task. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Chapter 3

Coca crops are surrounding my school. The Impact of Illicit Cultivation on Elementary Rural Education in Colombia

Darwin Cortés, Omar Garzón and Nazly López-Peña

3.1. Introduction

Education is widely recognized as a fundamental driver of social and economic development. Ensuring adequate conditions for educational attainment from the earliest levels is crucial for individual progress and the accumulation of human capital, ultimately contributing to the reduction of development gaps across regions and countries (N. Angrist et al., 2019; Becker, 2010; Mincer, 1974). Among the many determinants of educational success, infrastructure quality, safety, and healthy learning environments play an important role (Nwakpa et al., 2024; Pickett et al., 2022; Schneider, 2002; Srivastava and Jaiswal, 2022).

Given Colombia's long-standing history with coca and cocaine production, and the wide range of policies implemented to mitigate their effects, much research has examined the broader socioeconomic impacts of illicit crop cultivation (Ladino et al., 2021; Llanes et al., 2024; J. C. Muñoz-Mora et al., 2018; Prem et al., 2021). Yet, few studies have explored how these dynamics affect schools, potentially undermining the environment and conditions necessary for effective learning during the early stages of education. For instance, Martin (2023) analyzes the effect of coca production on child labor following the implementation of the *National Illicit Crop Substitution Program* (PNIS, for its Spanish acronym) in Colombia. Similarly, Dammert (2008) documents the consequences of the geographic shift of coca production from Peru to Colombia on child labor and schooling outcomes, while Manrique López and Contreras (2025) study the effects of coca eradication policies on education, also in the Peruvian context. In Colombia, Angulo (2024) evaluates the impact of the suspension of aerial spraying policies for coca eradication on educational outcomes at the municipal level in Colombia.

In response to the expansion of coca cultivation in Colombia during the late 1990s, the national government, in cooperation with the United States, implemented a series of anti-drug policies, beginning with *Plan Colombia* in 2000. Despite these efforts, coca cultivation has remained as a persistent concern, particularly because illegal armed groups and criminal organizations in the country have relied on coca and cocaine production as a primary source of financing (Díaz and Sánchez, 2004;

Prem et al., 2021).

Later, in 2012, former President Juan Manuel Santos initiated peace negotiations between the national government and the *Revolutionary Armed Forces of Colombia* (FARC, for its Spanish acronym), one of the most powerful guerrilla groups in the country. The resulting Peace Agreement was structured around six key points, one of which focused on substituting illicit crops through the PNIS. Although the program was not officially launched until 2017, its early announcement in 2014 functioned as a *perverse* incentive, encouraged both coca and non-coca growers to begin or expand coca crops in anticipation of qualifying for program benefits. This incentive structure contributed to a shocking 43.5% increase in coca cultivation in 2014 relative to 2013 levels, and to an average increase of 37% in cultivated hectares between 2014 and 2017 (SIMCI, 2022).

Given this framework, our study examines the impact of coca cultivation near schools on key educational outcomes, specifically enrollment, dropouts, and academic failure (the latter serving as a proxy for academic performance). We analyze these effects both at the aggregate school-level and disaggregated by schooling level. The sharp increase in coca cultivation after the PNIS announcement offers a unique opportunity to examine how illicit crop dynamics can disrupt educational environments and compromise students' schooling trajectories.

Taking advantage of georeferenced school location data, we construct circular buffers with a radius of $1km$ and $5\ km$ around each school, using the school coordinates as centroids. We then identify and match all $1\ km \times 1\ km$ coca cultivation grids (each covering 100 hectares) that intersect with these buffer zones. Each grid reports the number of coca hectares cultivated within its $100\ ha$ area, allowing us to interpret the reported values as percentages of land used for coca cultivation. Since buffers may contain only a fraction of a given grid, we compute the proportion of each grid's area that falls within the buffer and weight the reported coca hectares accordingly.

This spatial approach enables us to measure temporal variation in coca cultivation hectares surrounding each school over the study period. By linking this information with administrative records from the *National Administrative Depart-*

ment of Statistics of Colombia (DANE, for its Spanish acronym), we track changes in educational outcomes for the schools identified as being exposed to coca cultivation.

Our hypothesis is based on the labor-intensive nature of coca cultivation, which requires a consistent supply of low-skilled and low-cost labor to maintain the crops, harvest the leaves, and process them into paste (Dirección de Antinarcóticos, 2014). Due to its high harvesting frequency, typically between four and six cycles per year, this activity (i) attracts a highly mobile and informal labor force that often migrates across regions in response to wage differentials or (Gutiérrez-Sanín, 2021; Sviatschi, 2022), and (ii) in many cases, children and teenagers of coca-growers or coca-scrappers gradually become involved in the cultivation process, either directly as laborers or indirectly through family engagement.

Anecdotal reports describe entire families, including school-aged children, participating in coca harvesting during peak periods (AFP, 2021; InSight Crime, 2020). In this context, the expansion of coca cultivation is associated with increased school dropout rates and reductions in school enrollment, particularly in settings where labor market incentives and weak institutional enforcement reduce the opportunity cost of abandoning school (J. Angrist and Kugler, 2008; Dammert, 2008; Mejía and Restrepo, 2013; Rodriguez, 2020).

Coca cultivation is predominantly concentrated in isolated and rural regions located along Colombia's agrarian frontiers (J. Muñoz-Mora et al., 2018), where poverty rates consistently exceed national averages and access to legal markets is severely limited. In these areas, illegal armed groups often impose alternative forms of territorial control and social order, restricting communities to a narrow set of economic and social activities (AFP, 2021; Dirección de Antinarcóticos, 2014; InSight Crime, 2020). Within this constrained environment, coca-related activities represent the primary source of household income. As a result, economic survival frequently becomes intertwined with informal and illicit labor dynamics, including the participation of children and teenagers in cultivation and processing tasks (Ciro, 2020; Dion and Russler, 2008; Edmonds and Pavcnik, 2005; Rodriguez and Torres, 2009).

To identify causal effects, we implement a difference-in-differences strategy. However, we are aware that coca cultivation in Colombia follows a heterogeneous and non-random trajectory, shaped by local conditions and strategic decisions. In particular, the pre-announcement of the PNIS in 2014 introduced variation not only in whether coca was cultivated, but also in the timing and intensity of its expansion. Rather than a sharp treatment onset, the policy induced staggered and continuous changes across units. To account for this complexity, we adopt the extended DiD framework by Chaisemartin and D'Haultfœuille (2024) (DiD_ℓ) that accommodates treatment heterogeneity over time and intensity levels, allowing us to capture the dynamic and non-binary nature of coca cultivation surrounding schools.

In our context, a standard Two-Way Fixed Effects (TWFE) difference-in-differences design is not robust to treatment heterogeneity. Schools are exposed to multiple changes in the intensity of coca cultivation in their surroundings, meaning that, within the same period, a school may experience increases, decreases, or extinction in exposure (i.e., the treatment can *switch on* or *switch off*). Under such circumstances, the TWFE estimator suffers from a contamination problem; it implicitly compares treated units to other treated units at different stages or intensities of treatment.

To assess the extent of this issue in our case, we implement the decomposition of TWFE weights proposed by Chaisemartin and D'Haultfœuille (2020) and find that 46% of the Average Treatment Effects on the Treated (ATTs) receive negative weights. This implies that a substantial portion of the estimator is driven by comparisons in which the TWFE estimator treats schools with above-average coca intensity as the *treated* group and those with below-average intensity as the *controls*, assigning weights proportional to their distance from the mean. This re-scaling distorts the interpretation of the treatment effect, particularly when exposure varies continuously and non-randomly across units (Callaway et al., 2024).

The DiD_ℓ estimator measures the effect of a change in treatment intensity ℓ periods after the initial treatment change (*switch on*). For each school that experiences a change in coca exposure (a *switcher*), the estimator compares the evolution of educational outcomes between the period before the change and ℓ periods after it, relative to a group of schools who have not yet changed their treatment (*stayers*), and share the same baseline (period-one) coca exposure level. To this extent, the resulting estimate captures the average effect of having been exposed to a higher coca exposure intensity for ℓ periods, under a conditional parallel trends assumption between *switchers* and *stayers* with the same baseline exposure.

Moreover, we opt for the dynamic version considering that our objective is not only to estimate the average effect of a change in the treatment for each school, but also to trace its intertemporal evolution across periods following the initial change (year-one). With the static version, the estimator recovers an ATE by pooling the effects across all post-treatment periods and treatment intensities. This aggregation masks the timing and potential heterogeneous dynamic response to treatment, which becomes one of our major interests for our case.

This study contributes to the growing literature on the effects of illicit coca cultivation dynamics on childhood outcomes, particularly in the Colombian context. Several recent studies have explored the relationship between coca-related policies and educational or labor outcomes. For instance, Angulo (2024) finds that the suspension of aerial spraying policies for coca eradication in 2015 led to an effect of a 0.3 standard deviation increase in high-school dropout rates for each 1% increase in coca cultivation area, his work observes a similar decrease in academic retention, and no significant effect on enrollment. Similarly, Rodríguez (2020) shows that between 2008 and 2012, aerial spraying increased the likelihood that older siblings in coca-growing areas would leave school by 0.15 percentage points, and raised the dropout probability of their younger siblings by five percentage points. In a related study, Martín (2023) demonstrates that following the pre-announcement of the PNIS, children in historical coca-producing municipalities became four percentage points more likely to work; however, the associated reduction in hours worked per child had no effect on schooling outcomes.

In a broader regional context, Dammert (2008) finds that the shift of coca production from Peru to Colombia between 1997 and 2000 was associated with an 18% to 40% increase in child labor in Peru's coca-growing regions. Similarly, Sviatschi (2022) shows that, following the resurgence of illicit coca activity in areas with suitable growing conditions, Peruvian households increased their reliance on child labor for coca farming. This early involvement in criminalized agricultural activities had long-term consequences: affected children were found to be 30% more likely to be incarcerated as adults for violent or drug-related offenses.

Our baseline results indicate that a 1% increase in coca cultivation within 1 *km* of schools is associated with a decline of approximately 0.06 standard deviations in enrollment and a nearly 0.13 standard deviations increase in dropout rates. These effects emerge immediately following the initial change in coca cultivation intensity. For enrollment, the negative impact intensifies over the following periods. In contrast, the rise in dropout rates is statistically significant one period after the treatment *switch*, but tends to stabilize in the following periods.

The paper is structured as follows: Section 3.2 provides a context for the coca dynamics in Colombia and their relationship to families' livelihoods, which impacts children and teenagers. Section 3.3 discusses the data used in our analysis and how our variables of interest are constructed. We present some descriptive statistics in Section 3.4 and our empirical strategy is described in Section 3.5. Section 3.6 presents our main results, and Section 3.7 discusses the mechanisms underlying these results and provides a conclusion.

3.2. Context

3.2.1. The dynamics of coca crops in Colombia

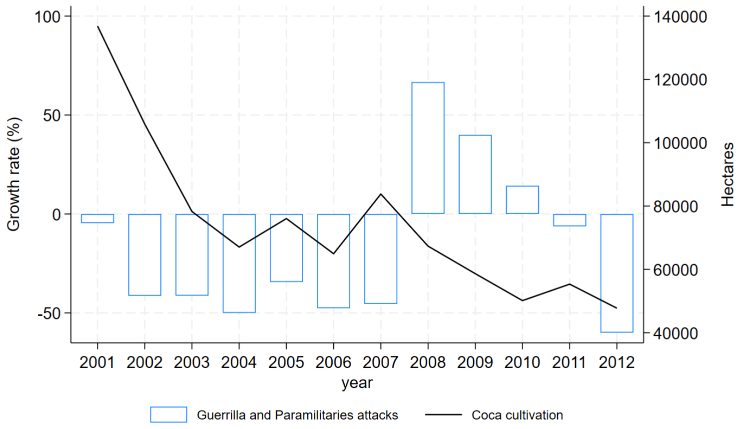
Coca leaves are the primary raw material used in the production of cocaine. Their cultivation, processing, and trafficking require specific climatic and geographical conditions, typically found in the agricultural frontier of rural regions, where there is a lack of law enforcement, abundant natural resources, and high prevalence of poverty (J. Muñoz-Mora et al., 2018).

Colombia, Peru and Bolivia are host to more than 98% of the global land area planted with coca (Moreno-Sánchez et al., 2003). Virtually the entire global supply of cocaine originates in South America, primarily from those countries (Manrique, 2025; UNODC, 2023). In the 1970s, most coca cultivation took place in Peru and Bolivia, while the product was refined in Colombia. However, with the rise of powerful drug cartels in Colombia during the 1980s, the country's role in coca production expanded. By the late 1990s, Colombia had surpassed its neighbors in coca cultivation, and by 1997, the area dedicated to coca bushes in Colombia exceeded that of both Peru and Bolivia (UNODC, 2010). Today, Colombia accounts for the region's largest share of coca bush cultivation (UNODC, 2023).

In response to the expansion of coca cultivation in the late 1990s, the governments of Colombia and the United States launched *Plan Colombia* in 2000, a bilateral initiative aimed at combating drug production and strengthening state presence in coca-growing regions. The plan also sought to reduce the international supply of illicit drugs, particularly in the United States and Europe. This policy marked a turning point in Colombia's drug control strategy, which increasingly relied on a combination of forced eradication, aerial spraying with pesticides, military intervention, and social development programs (Departamento Nacional de Planeación, 2006).

Figure 3.1 illustrates the dynamics in coca cultivation between 2001 and 2012. Even with the program's efforts, during the plan's second phase (initiated in 2005), there was a temporary rise in coca cultivation, with noticeable increases between 2004–2005 and 2006–2007. By 2007, Colombia already accounted for 70% of the world's total coca crops (UNODC, 2006). This last period also coincided with a rise in violent attacks perpetrated by guerrilla and paramilitary groups, as coca cultivation and cocaine production in Colombia, together with trafficking to the United States and Europe, had become their primary source of funding (Díaz and Sánchez, 2004; Prem et al., 2021).

Figure 3.1: Coca cultivation and violent attacks (2001-2012)



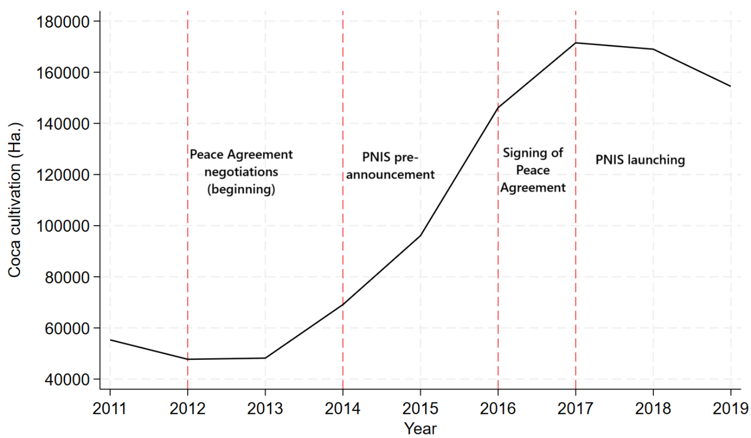
Note: Author's calculations. Source: SIMCI-ONUDC and Centro Nacional de Memoria Histórica

Among several reasons, former President Juan Manuel Santos initiated peace negotiations in 2012 between the Colombian government and the *Revolutionary Armed Forces of Colombia* (FARC, for its Spanish acronym), one of the country's oldest and most powerful guerrilla groups. The resulting Peace Agreement was structured around six core points, the third one focused specifically on the substitution of illicit crops such as coca. This initiative was proposed through the *Integral Substitution of Illicit Crops* (PNIS, for its Spanish acronym), a national program aimed at promoting voluntary crop substitution in coca-growing regions, rather than the forced eradication and aerial spraying methods (Cancillería de Colombia, 2016).

Between the start of the peace negotiations and the signing of the agreement in 2016, the Colombian government pre-announced the PNIS in May 2014, inducing anticipation effects among coca growers communities, the main program beneficiaries. This early announcement generate sort of a *perverse* incentive for a strong expansion of coca cultivation both among prospective beneficiaries and neighboring farmers (IPSOS & UniAndes, 2023; Ladino et al., 2021; Prem et al., 2021), with a growth rate of 43.5% in 2014 relative to 2013 levels (Figure 3.2).

Following the official signing of the Peace Agreement, the national government formally launched the PNIS in January 2017. The program set an ambitious target of substituting 50,000 hectares of coca crops in its first year and stated a phased payment scheme to participating households. However, payments were neither delivered on time nor with the expected frequency, leaving many families financially vulnerable in the face of the abrupt income shock caused by the coca bushes eradication[1] (IPSOS & UniAndes, 2023). Finally, for 2018 the national government under President Iván Duque decided not to expand the program to include additional beneficiaries (Fundación Ideas para la Paz, 2019).

Figure 3.2: Coca cultivation (2001-2019)



Note: Author's calculations. Source: SIMCI-ONUDC.

3.2.2. The demographics of Coca crops

There are several types of actors involved in coca cultivation. Among them are producers, who possess land and may or may not come from a traditional agricultural background, and collectors or leaf scrappers, commonly known as *raspachines*, who do not own land but actively participate in both the cultivation and processing of

[1]The enrollment and participation of families in the PNIS included a conditional cash transfer component, consisting of monthly payments of COP $ 1,000,000 over a 12-month period to support the economic livelihood of participating households. It is worth noting that the program delivers these transfers on a bimonthly basis, resulting in a total of six payment cycles of COP $ 2,000,000 each UNODC, 2019.

coca and its derivatives. Coca cultivation is highly unskilled, labor-intensive, and the harvesting is done manually, and can yield between four and six harvests per year (depending on the variety of the bush). *Raspachines* often work in fields greater than 1 hectare, which requires around 51 days of work for the coca crop maintenance[2]. In this process, one hectare of coca is harvested in approximately ten labor days, and they can scrap between 92 and 138 kg of coca leaves per day. After the first harvest, subsequent harvests (known as *raspas*) are carried out periodically every three months (Dirección de Antinarcóticos, 2014). As a result, each harvest requires a substantial labor force, attracting workers from various regions (Gutiérrez-Sanín, 2021; Sviatschi, 2022).

Raspachines are often incentivized to migrate both inter and intraregionally in search of coca cultivation and harvests. This high degree of mobility is primarily driven by fluctuations in regional labor market wages and the displacement of coca crops as a consequence of the state's interdiction measures (Ministerio de Justicia y del Derecho & UNODC-SIMCI, 2012). For 2014, approximately 65,000 households, composed of five individuals, earned an average annual income of around US$1,160 per capita, and in 2021, in the southern department of Cauca, a coca leaf scrapper could earn up to US$37 per day, compared to the US$8 daily income associated with Colombia's minimum wage (Fundación Ideas para la Paz & UNODC, 2018; UNODC, 2015, 2019).

The demand for labor has turned coca cultivation into a seasonal source of economic security for both cultivators and *raspachines*. Similar to traditional agricultural cycles, collectors often migrate in accordance with the harvest calendar, sometimes even relocating with their families. Anecdotal evidence has documented how entire families participate in coca leaf harvesting; they often migrate to coca-growing regions and settle in improvised camps near the plantations, including single mothers with children, elders, and even Venezuelan migrants (AFP, 2021). In this context, the youngest are also quickly involved in coca cultivation labor, which

[2]Collectors' tasks typically include deforestation, land preparation, planting, the manual scraping of the coca leaves, and the storage and transportation of inputs (Ministerio de Justicia y del Derecho & UNODC-SIMCI, 2012).

is associated with elevated school dropout rates (Fundación Ideas para la Paz & UNODC, 2018; UNODC, 2015, 2019).

Coca cultivation is more prevalent in underdeveloped and geographically isolated regions within Colombia, where limited access to legal markets restricts the viability of alternative agricultural activities. As a result, poverty tends to be more severe in these areas, mainly rural, where coca-related activities often constitute the primary source of economic livelihood for marginalized and vulnerable peasant populations. In this context, extremely poor farmers are significantly more likely to engage in coca cultivation than their non-poor counterparts living in the same regions (Ciro, 2020; E. Dávalos and L. M. Dávalos, 2020; Dion and Russler, 2008), which is linked with child labor, unsatisfied basic needs, and limited access to social public services (Edmonds and Pavcnik, 2005; Ray, 2000; Rodriguez, 2020).

As observed, coca cultivation dynamics in Colombia have evolved into a complex and heterogeneous cycle that is not random. However, in the country's recent history, the events surrounding the Peace Agreement, particularly the pre-announcement of PNIS in 2014, have had a substantial impact on the variation and expansion of coca crops.

Anticipation effects and the pre-announcement of the PNIS

Several studies have documented the social and economic impacts triggered by the pre-announcement of the PNIS, which has been widely characterized as problematic due to the anticipation effects it generated. In particular, the announcement created strong incentives for individuals and households to initiate or expand coca cultivation with the expectation of qualifying for the program's economic benefits.

Empirical evidence supports this interpretation. Following the PNIS announcement in 2014, coca cultivation increased significantly in historically affected regions. Marín (2024) finds that this expansion contributed to a 2.5% to 3.1% increase in municipality-level GDP, reflecting the substantial economic weight of coca cultivation in local economies. Ladino et al. (2021) find a 0.54 percentage point increase in coca planting as a direct anticipation effect in municipalities with historical FARC guerrilla presence. Prem et al. (2021) further show that a one-standard-deviation increase in coca suitability translates into an increase of nearly one-quarter of a standard deviation in coca cultivation after the policy announcement.

These findings suggest that the pre-announcement introduced a quasi-experimental variation in coca-growing behavior across regions and over time. In this context, we exploit this exogenous source of variation as a key component of the identification strategy. The policy announcement acted as a policy shock, differentially affecting schools located in municipalities considering their ex-ante exposure to coca cultivation. This variation is plausibly exogenous to educational outcomes in the short term and allows for causal inference on the impact of coca expansion on indicators such as school enrollment, dropout, and school failure.

3.2.3. Childhood and education in the shadow of coca bushes

As previously discussed, coca cultivation in Colombia is concentrated along the agricultural frontier, particularly in highly dispersed and isolated rural areas. According to the *National Administrative Department of Statistics* (DANE for its Spanish acronym), by 2017, approximately 23.3% of the Colombian population lived in rural zones, and these zones cover more than 80% of the national territory. Despite the vast geographic reach of these regions, rural education faces significant structural challenges, such as limited school coverage and low student retention rates (MEN, 2015). In that same year, 66.6% of schools in the country were located in rural areas, commonly covering the initial stages of education, 47.8% provided elementary education, and 38.4% pre-school. The dropout rates in those areas reached approximately 4%, compared to 2.7% in urban zones (DANE, 2023). In addition, the average years of schooling reached six in rural areas, far below the 9.7 years reported in urban contexts (MEN, 2022a). These dynamics, along with other challenges, reinforce the rural-urban disparity from the primary levels of education, particularly for those living in highly dispersed coca-growing regions.

Child labor has been closely associated with the dynamics of crops in coca-growing areas. For example, between 1997 and 2013, rising coca prices led to a 30%

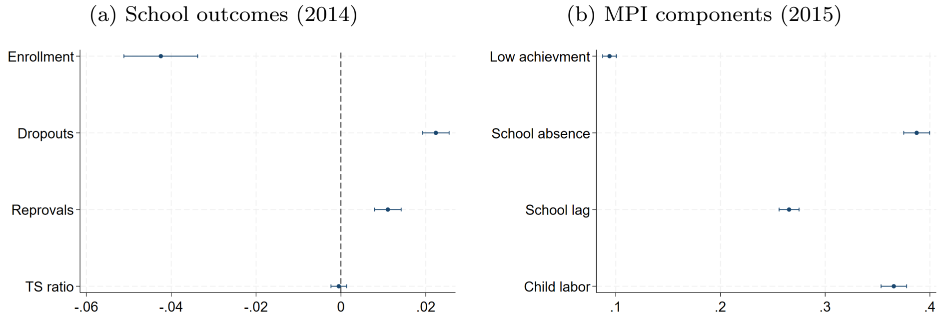
increase in child labor in areas highly suitable for coca cultivation in Peru (Sviatschi, 2022). In the case of Colombia, evidence from 1997 shows an increase in labor supply among teenage boys, accompanied by a simultaneous decline in school enrollment in coca-producing regions (J. Angrist and Kugler, 2008).

In other scenarios, eradication policies such as aerial spraying, implemented between 2008 and 2012, were linked to a one-percentage-point increase in the likelihood that children would work instead of attending school (Rodriguez, 2020). More recently, following the announcement of the PNIS, children living in municipalities with a history of coca production became nearly four percentage points more likely to engage in labor (Martin, 2023).

Consequently, higher school dropout rates are commonly observed in coca-growing regions, often accompanied by decreases in school enrollment. In these areas, students frequently abandon their studies to work in coca production, particularly in activities related to coca leaf processing, or spend their free time after school working in the coca fields (Centro Nacional de Memoria Histórica, 2018). This pattern is further reinforced by parents who view their children's participation in coca-related labor as a necessary source of financial support for the household (Dirección de Antinarcóticos, 2014). Furthermore, changes in coca production or the shifting of crops to new locations are also linked to the working hours of children living in coca-growing areas, as in the Peruvian case (Dammert, 2008). In this respect, Sviatschi (2022) shows that children who work in the coca fields are 30% more likely to get involved in crime and violence.

Figure 3.3b highlights that schools located in municipalities with a historical presence of coca cultivation tend to be more vulnerable across several dimensions of the *Multidimensional Poverty Index* (MPI). These schools are generally located in municipalities with lower educational achievement, higher classroom absenteeism, greater school lag, and, as documented, a higher incidence of child labor. This environment allows us to assume that students and their families are vulnerable to migrating regionally in search of work during the coca harvest, potentially increasing the probability of dropouts and decreasing school enrollment.

Figure 3.3: Mean differences by coca cultivation exposure



Panel A reports the average differences between schools unaffected by coca cultivation and those exposed to it, whereas Panel B shows the differences between schools situated in non-coca and coca-growing municipalities.

Along with this, violence tends to be more severe in coca-producing and trafficking areas (J. Angrist and Kugler, 2008; Mejía and Restrepo, 2013), prompting many parents to keep their children out of school due to safety concerns (Torrado, 2022). This, in turn, contributes to declines in school enrollment and makes them enter the labor market too early (InSight Crime, 2020; Rodriguez and Torres, 2009).

On the other hand, school enrollment can also respond differently to various anti-drug policies. Carvajal (2023) finds that following the suspension of aerial pesticide spraying (specifically Glyphosate) in 2015, school dropout rates declined in municipalities that had been exposed to spraying between 2010 and 2015, compared to those that had not. The effect is particularly pronounced among elementary and sixth-grade students, and is stronger for boys than for girls.

Moreover, the school's infrastructure in these areas is precarious, often forcing communities to finance part of its maintenance themselves (InSight Crime, 2020). These regions not only lack basic public services and access to clean drinking water, but are also frequent targets of violent attacks between armed groups or hotspots for illegal recruitment. As a result, students face constant vulnerability (Defensoría del Pueblo de Colombia, 2020; InSight Crime, 2020), and many teachers are forced to abandon their schools due to threats against them (Centro Nacional de Memoria

Histórica, 2018).

3.3. Data

This study relies on a panel dataset of schools georeferenced across multiple municipalities, observed over several years surrounding the 2014 pre-announcement of the PNIS. The dataset includes both schools exposed and not exposed to coca cultivation, classified by the presence and intensity of coca cultivation within various buffer distances (1 *km* and 5 *km*) around. Educational outcomes, including enrollment, dropout, and failure rates, are observed each year from 2013 to 2019.

3.3.1. Schools and education outcomes

Our analysis focuses on three key basic education outcomes: dropout rates, failure rates, and enrollment. These indicators are reported annually by schools through the C-600 census survey, administered by the *National Administrative Department of Statistics* (DANE, for its acronym in Spanish) in coordination with the *Ministry of National Education* (MEN, for its acronym in Spanish)[3] (DANE, 2023). Enrollment data encompass the sum of students who drop out, pass, or fail during the academic year.

As in other studies, such as Angulo (2024), which examines the effects of coca cultivation on educational outcomes at the municipality-level, enrollment is often measured as the proportion of students relative to the school-age population of the municipality. While this approach is appropriate when the unit of analysis is the municipality, it becomes problematic in our case, where the observation unit is the individual school. Applying a municipality-level enrollment rate conflates school-specific outcomes with broader demographic dynamics that are external to the school and may fluctuate for reasons unrelated to the treatment, such as changes in population structure. For example, a school may maintain stable enrollment numbers

[3]C-600 survey is an annual census, targeted at both public and private educational sites offering preschool, primary, lower secondary, and upper secondary education levels, including adult education through integrated special learning cycles and flexible educational models, located in both urban and rural areas throughout the national territory.

while its proportional coverage appears to decline simply because the municipality experienced an increase in school-age population, an effect that does not reflect a deterioration in either the capacity or dynamics of the school. On the other hand, both school dropout and failure rates are then calculated as a proportion of enrollment in each school.

By examining their temporal variation, we assess how these outcomes evolve in schools located near coca cultivation areas. We have geographical coordinates that enable us to identify schools located in areas exposed to coca cultivation. Using this geospatial data, we create buffer zones of 1 *km* and 5 *km* around each school to capture varying degrees of exposure to coca cultivation. This spatial matching enables us to categorize educational institutions based on their proximity to illicit crop areas. By linking this spatial information with administrative educational data, we can estimate how exposure to coca-growing environments influences school attendance patterns and academic outcomes over time.

It is important to clarify that, although enrollment is reported in year t, dropout rates are recorded in year $t+1$. This is because students enroll at the beginning of the year t, but may drop out or relocate to other schools at any point during that same year (MEN, 2022b). For consistency in the analysis, we lag the dropout data from $t+1$ back to t, aligning it with the enrollment year during which the dropout event occurred.

The data also includes additional information, such as whether the school is located in a rural or urban area, enrollment, dropout, and failure rates disaggregated by education level, teachers-students ratio, among other variables.

3.3.2. Coca illegal crops

Our second source of variation is based on the number of hectares of coca crops located within 1 *km* and 5 *km* buffers around each school[4] for the mentioned period. Coca crop data are represented in grid squares of 1 $km \times 1$ km. This information corresponds to satellite-based estimates of the coca-covered area reported annually since 2000

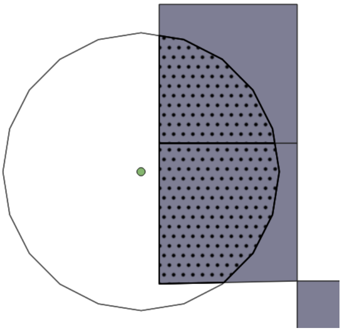
[4]We exclude the department of San Andrés and Providencia, an island territory located in the north of the country.

by the *Integrated Illicit Crop Monitoring System* (SIMCI for its Spanish acronym) of the *United Nations Office on Drugs and Crime* (UNODC). The methodology employed by SIMCI is based on remote sensing principles, whereby energy from a source, such as sunlight, is reflected by the Earth's surface and captured by a sensor onboard satellites. This information then undergoes a series of digital and visual processing steps that enable the identification, spatial mapping, and measurement of illicit crops (Llinás Rivera, 2005).

By georeferencing these data and overlaying them with the defined school buffer zones, we compute the proportion of 1 km^2 coca crop grid cells that intersect each buffer radius, which serves as a measure of exposure to coca cultivation. Figure 3.4 illustrates a school centroid surrounded by a 1 km circular buffer.

The use of a circular buffer ensures that all points along the boundary are equidistant from the centroid, providing a more realistic representation of the school's immediate surroundings. As shown in Figure 3.4, the coca crop grids are not always fully contained within the school buffer zones. To address this, we calculate the proportion of each 1 km^2 grid cell that falls within each buffer. Each grid cell reports the number of coca hectares, with a maximum of 100 hectares per cell (1 $km^2 = 100\ ha$). This allows us to interpret the values as a percentage of land cover. Accordingly, we weight each cell by the proportion of its area that lies within the buffer to obtain a more precise measure of coca exposure.

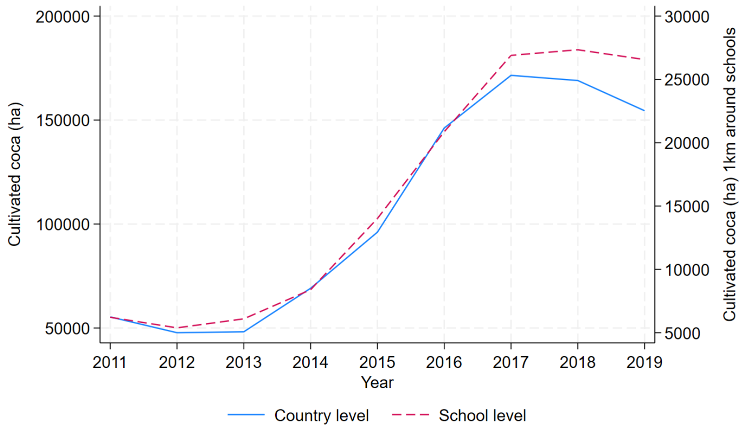
Figure 3.4: Geospatial overlay of schools and coca crop grids



For each grid cell, we compute the proportion of its area that falls within the radius of each school and multiply it by the total area of the grid. We interpret this proportion as the expected number of coca hectares surrounding the school, taking into account the heterogeneous distribution of coca bushes within each grid cell.

It is essential to acknowledge the limitations inherent in satellite-based estimates, particularly regarding the assumptions of within-cell homogeneity in coca density. Our measures can be valuable approximations of the spatial distribution of coca crops; nevertheless, to address potential measurement error and validate the robustness of our results, we also estimate the variation in the number of coca grid cells around each school, regardless of the reported coca density inside the grid. Figure 3.5 illustrates that the evolution of coca cultivation within 1 km buffers surrounding schools closely follows the national trend, suggesting that local exposure reflects broader patterns of coca expansion.

Figure 3.5: Coca crops around schools (1 km) and national trend



Note: Author's calculations. Source: SIMCI-ONUDC and DANE.

3.4. Descriptive Statistics

Our dataset comprises a panel of schools located in both coca-cultivating and non-cultivating areas, spanning rural and urban settings. Although coca cultivation is predominantly concentrated in rural zones, some urban schools are also affected by nearby coca fields, in our case, they represent only 2,9% of the sample[5]. In our sample, approximately 20.4% of rural schools were affected by coca cultivation at some point between 2011 and 2019, representing approximately 12.5% of all schools in the country.

An additional feature in our sample relates to the high representativeness of schools that cover pre-school and elementary education levels. In Colombia, most rural schools predominantly serve students at the elementary level, while upper levels of education are typically offered in the urban centers of municipalities (MEN, 2001). As a result, younger children in rural areas may be more vulnerable to local shocks in the dynamics of coca cultivation. Figure 3.6 shows that during our analysis

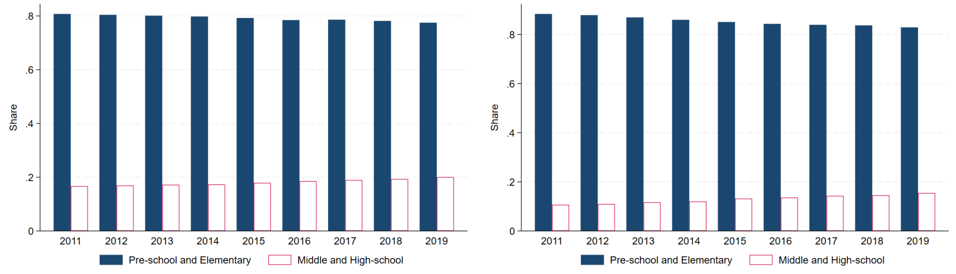
[5]98% of the schools exposed to coca cultivation are situated in municipalities classified as either *Programas de Desarrollo con Enfoque Territorial* (PDET) or *Zonas Más Afectadas por el Conflicto Armado* (ZOMAC), categories established by the Colombian government to identify regions historically affected by armed conflict and the prevalence of illicit coca production.

period, these schools cover approximately 80% of our sample (Panel A), and this share increases to 85% if we consider those in which coca crops are present (Panel B). Our sample distribution enables us to analyze a case in which most of the effects potentially affect students in elementary education levels more than those in middle or high school.

Figure 3.6: Distribution of rural schools by education levels in Colombia (2011-2019)

(a) Schools in rural areas

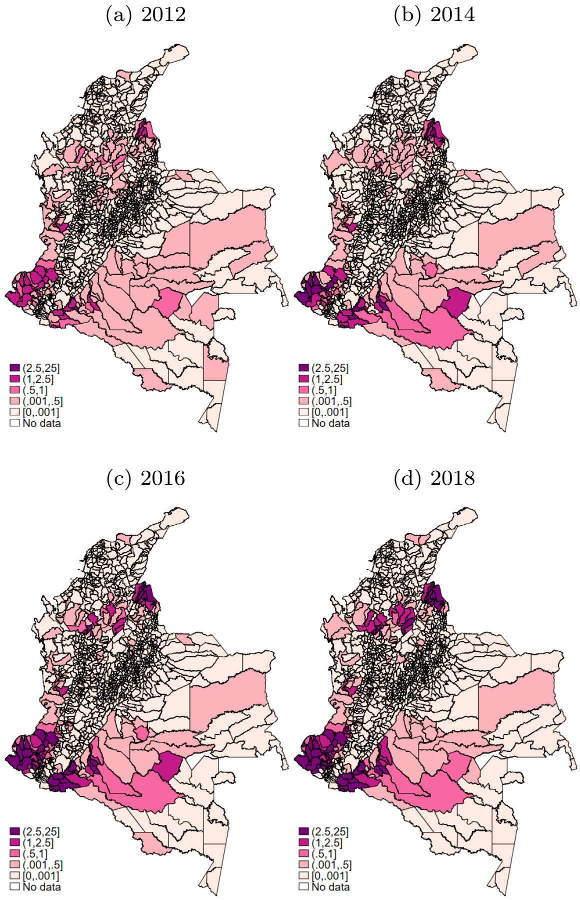
(b) Coca influenced schools in rural areas (1 *km*



Figures show the share of schools that cover both education levels. Pre-school and elementary levels encompass the first five years of formal education, while middle and high school levels cover the subsequent six years. Source: C-600 Survey DANE, 2019

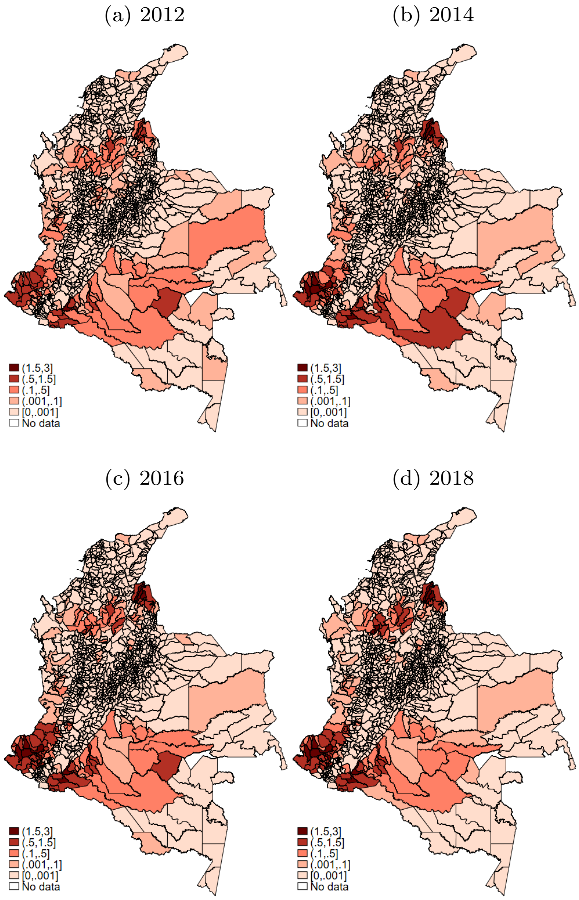
Figures 3.8 and 3.7 illustrate the evolution of the mean coca cultivation, measured both in hectares and in the number of cultivation grids, within a 1 km radius around schools, at the municipality level. The maps reveal a clear intensification pattern in both measures before, during, and after the 2014 pre-announcement of the PNIS. This spatial concentration of illicit crops around schools suggests a widespread exposure of students to the economic and social dynamics associated with coca cultivation, which may plausibly affect their educational outcomes. In particular, Figures 3.8b and 3.7b highlights a notable and gradual increase in the number of coca cultivation grids in 2014, suggesting that coca expansion around schools occurred not only through intensification within existing cultivation areas, but also through the incorporation of new ones, reflecting both intensive and extensive margin effects.

Figure 3.7: Number of cultivated coca (ha) sorrounded schools (mean at municipality-level)



Note: Maps display the mean number of coca cultivation hectares located within a 1 km radius of each school in the sample, at the municipality level. Source: SIMCI-ONUDC.

Figure 3.8: Number of coca grid's surrounded schools (mean at municipality-level)



Maps show the mean number of coca cultivation grids located within a 1 km radius of each school in the sample, at the municipality level, irrespective of the coca density within each grid. Source: SIMCI-ONUDC.

Table 3.1 presents educational outcomes for the subset of schools identified as being influenced by coca cultivation, disaggregated by buffer size. The data reveal an inverse relationship between enrollment and coca cultivation, with the decline in enrollment being particularly pronounced between 2012 and 2014. In contrast, both school dropout and failure rates appear relatively stable over time and across buffer sizes.

Figure A1 in the Appendix also reveals significantly distinct patterns in educational outcomes between influenced and non-cocaine-influenced schools over time. On average, enrollment is consistently lower, and dropout rates are higher in exposed schools across all periods. Additionally, failure rates are significantly higher in coca-influenced schools before and during the PNIS pre-announcement period, though this difference appears less pronounced thereafter.

Table 3.1: Descriptive statistics of school-related outcomes by buffer size

	1 km Buffer			5 km Buffer		
	N	Mean	SD	N	Mean	SD
Panel A. Enrollment						
2012	4,769	61.33	118.40	7,905	84.51	184.57
2014	4,524	57.78	118.52	7,749	81.97	179.94
2016	4,586	57.99	120.56	7,713	81.89	183.84
2018	4,698	54.79	115.91	7,818	78.32	177.76
Panel B. School dropout						
2012	4,170	0.07	0.12	7,037	0.07	0.11
2014	4,387	0.07	0.12	7,488	0.06	0.11
2016	4,511	0.06	0.11	7,566	0.06	0.10
2018	4,530	0.05	0.11	7,552	0.05	0.10
Panel C. School failure						
2012	4,170	0.08	0.12	7,037	0.08	0.14
2014	4,387	0.07	0.12	7,488	0.07	0.11
2016	4,511	0.06	0.10	7,566	0.06	0.09
2018	4,530	0.06	0.10	7,552	0.06	0.10
Panel D. Cultivated coca *ha*						
2012	5,337	1.01	2.76	9,061	15.21	39.61
2014	5,337	1.57	4.35	9,061	23.47	66.52
2016	5,337	3.91	9.56	9,061	57.95	166.01
2018	5,337	5.12	10.69	9,061	74.32	165.86

The table presents dropout and failure rates, computed as the proportion of reported enrolled students per school. Statistics are based on the subset of schools identified as being influenced by coca cultivation, with the number of such schools increasing as the buffer radius expands.

3.5. Identification Strategy

3.5.1. TWFE estimator

As mentioned, the announcement of the PNIS in 2014 introduced an anticipation effect that could have incentivized potential beneficiaries to initiate or expand coca cultivation, in order to qualify for the program. From this point, coca cultivation dynamics are not random and may respond to strategic decisions by cultivators, which leads us to exploit the 2014 pre-announcement of the PNIS as a source of exogenous variation on school-related outcomes.

A conventional TWFE design would be applied to this case, which requires a binary and sharply defined event on time that affects treated schools. However, in this context, treatment is neither binary nor affect all units at the same time. Coca cultivation intensity varies continuously across schools and time. Specifically, the anticipatory response of PNIS pre-announcement did not necessarily occur simultaneously and with the same intensity across crops; that is, some cultivators may have responded immediately, while others adjusted their behavior in subsequent years.

On the other hand, during this period, coca cultivation was also subject to dynamic and potentially reversible decisions by cultivators. While the pre-announcement of the PNIS may have encouraged the initiation or expansion of coca planting in anticipation of program eligibility, a range of factors (such as increased law enforcement activity or growing skepticism about whether the PNIS would ultimately fulfill its promised benefits) may have led some cultivators to reduce or abandon coca cultivation (Fundación Ideas para la Paz, 2025; Ortiz Fonnegra, 2024). As a result, schools may be exposed to coca cultivation in some years, while others may see reductions or even temporary exits from exposure, leading to heterogeneous treatment effects among units.

In our context, a TWFE design is not robust to the presence of heterogeneous treatment effects. Schools are not exposed to a single, binary treatment event, but instead experience multiple changes in the intensity of coca cultivation over time. This makes them *switchers* of the treatment, rather than simply *treated* or *untreated* units. Under such heterogeneity, TWFE estimators are subject to contamination. Additionally, each TWFE coefficient identifies a weighted sum of the treatment's effect with potentially negative weights that can erroneously be treated as *control* units (Callaway et al., 2024). To assess whether this issue arises in our setting, we implement the decomposition of weights proposed by de Chaisemartin and D'Haultfœuille, 2020 and find that 46% of the Average Treatment Effects on the Treated (ATTs) receive negative weights (see Table B1 of Appendix). This result indicates that the TWFE estimator is not robust to the heterogeneous effects of our treatment[6].

3.5.2. Continuous treatment estimator de Chaisemartin and D'Haultfœuille, 2024

Given these features and relying on recent extensions of the canonical DiD framework (see Callaway et al., 2024; de Chaisemartin and D'Haultfœuille, 2020), we implement the Chaisemartin and D'Haultfœuille (2023) difference-in-differences estimators DiD_ℓ strategy with continuous and time-varying treatment intensity (de Chaisemartin and D'Haultfœuille, 2024), since they are robust to heterogeneous and dynamic effects and contamination, using the `did_multiplegt_dyn` package. We chose DiD_ℓ estimator, among other new DiD estimators robust to heterogeneous treatment effects, because it applies to *unstaggered* designs in which treatments not only have a *switch on* (year-one treatment), but also might *switch off* again as in our case.

Theoretical setup

We adopt the framework and identification design proposed by Chaisemartin and D'Haultfœuille (2024) to our empirical setting. The estimator is applied to units (schools, s, in our case) observed over multiple years, t. For each school and year, we observe the school related outcomes variables $Y_{s,t}$, such as enrollment, dropout rates, or failure rates, which may be affected by coca cultivation in the surrounding area over time, i.e., the treatment $D_{s,t}$, which denotes the intensity of coca cultivation for school s in year t. Lets define $\mathbf{D}_s = (D_{s,1}, \ldots, D_{s,T})$ as the vector capturing the entire treatment history for each school s, and let $\mathbf{D} = (\mathbf{D}_1, \ldots, \mathbf{D}_S)$ define the collection of treatment trajectories for all schools S in the sample.

[6] As shown by de Chaisemartin and D'Haultfœuille, 2020, TWFE estimators identify weighted sums of treatment effects across groups and periods, where the weights may be negative. As a result, the estimated regression coefficient may differ substantially from the Average Treatment Effect (ATE) and even take the opposite sign, being negative while all the ATEs are positive.

As mentioned, coca cultivation is not randomly assigned. Following the PNIS pre-announcement in 2014, coca producers were incentivized to expand cultivation, leading to an increase in coca exposure around some schools in subsequent periods. Meanwhile, other schools experienced reductions or even a complete exit from exposure. As a result, the timing of the moment when a school is first exposed to a change (*switch*) in coca intensity varies across units. To account for this, define F_s as the first year in which school s experiences a change in treatment between 2014 and 2019.

With respect to the schools' related outcomes, for all the treatment values $(d_1, \ldots, d_t)$ from year-one to t, there are defined the potential school outcomes $Y_{s,t}(d_1, \ldots, d_t)$ at t if $(D_{s,1}, \ldots, D_{s,T}) = (d_1, \ldots, d_T)$, namely, those are the potential outcomes that schools would experience if its exposure to coca cultivation had followed the same sequence from year-one to year t. Now, $Y_{s,t} = Y_{s,t}(\mathbf{D}_s)$ corresponds to the realized treatment path of each s at t, which reflects the actual evolution of coca cultivation surrounding school s. Let

$$\delta_{s,\ell} = \mathbb{E}(Y_{s,F_s-1+\ell} - Y_{s,F_s+1-\ell}(D_{s,1}, \ldots, D_{s,1})) \tag{3.1}$$

be the expected difference between the observed outcome at year $F_s - 1 + \ell$ (i.e., ℓ years after the first treatment *switch*) and the counterfactual "status quo" (the *stayers*) outcome in schools that would have been observed if coca cultivation remained constant from year-one to $F_s - 1 + \ell$.

To estimate $\delta_{s,\ell}$, Chaisemartin and D'Haultfœuille (2024) propose a difference-in-differences estimator, DiD_ℓ, which compares the outcome evolution from the year immediately before the first treatment change ($F_s - 1$) to ℓ years after that change ($F_s - 1 + \ell$), between the *switcher* schools and those that have not yet experienced a change in coca cultivation by $F_s - 1 + \ell$ (*stayers*), and that shared the same level of coca cultivation hectares as the *switcher* schools in year-one.

The last consideration above is crucial for the validity of the parallel trends assumption underlying the estimator employed in this study. As emphasized by Chaisemartin and D'Haultfœuille (2025) and Callaway et al. (2024), there are two main advantages to conditioning on the initial treatment level in settings with continuous treatments. First, if *switcher* and *stayer* schools differ in their year-one treatment levels, comparing their outcome trajectories without adjustment implicitly assumes homogeneous treatment effects across all units, that is, that the treatment effect is constant across treatment intensities and over time. This is precisely the assumption made by the two-way fixed effects (TWFE) estimator. However, this assumption is particularly implausible in contexts such as ours. Second, when school outcomes are available for $F_s - 1$, the conditional parallel trends assumption can be assessed via a placebo test that compares the year $F_s - 1$ to 1 outcome evolutions of year 1-to-2 *switchers* and *stayers* (Chaisemartin et al., 2025).

Based on this setup, Chaisemartin and D'Haultfœuille (2024) define the Actual-Versus-Status-Quo (AVSQ) effect as the difference in outcome evolution between *switchers* and *stayers*. Specifically, for each switching school s, there exists a not-yet-influenced school s' (a *stayer*) such that $D_{s',1} = D_{s,1}$ and whose coca cultivation around the unit has remained unchanged since the beginning of the panel. The comparison is made up to the last years before s experiences a treatment change. Under this scenario, let

$$\delta_{s,\ell} = \mathbb{E}\left[Y_{s,F_s-1+\ell} - Y_{s,F_s+1-\ell}(D_{s,1},\ldots,D_{s,1})|\mathbf{D}\right] \tag{3.2}$$

be the estimated difference between the actual outcomes of s in $F_s - 1 + \ell$ (*switcher*) and its *status-quo* counterfactual (*stayer*) conditional to the treatment *switch*, from year-one to year $F_s - 1 + \ell$. For this purpose, $\delta_{s,\ell}$ is estimated using a difference-in-differences estimator, DiD_ℓ, defined as follows:

$$DiD_{s,\ell} = Y_{s,F_s-1+\ell} - Y_{s,F_s-1} - \frac{1}{N^s_{F_s-1+\ell}} \sum_{s':D_{s',1}=D_{s,1},F_{s'}>F_s-1+\ell} (Y_{s',F_s-1+\ell} - Y_{s'}, F_s - 1) \tag{3.3}$$

That is, DiD_ℓ compares the outcome evolution of coca influenced school s from the year before the treatment change $(F_s - 1)$ to ℓ years after the change $(F_s - 1 + \ell)$, with that of its counterfactual schools s' that (i) had the same level of coca cultivation in period one ($D_{s',1} = D_{s,1}$), and (ii) experienced no change in coca exposure over the entire period from 1 to $F_s - 1 + \ell$. In this case, it is important to consider two main assumptions, i.e., the no-anticipation effect, in which school outcomes do not depend on future treatments, and the Parallel trends assumption, which requires that at least two observational units have the same year-one treatment, so they can be comparable and expect to have the same expected evolution in outcomes. If the face of no-anticipation effect and parallel trends assumption is fulfilled, for every coca influenced school in time t, we can find an estimator for $\delta_{s,\ell}$ such that $\mathbb{E}\left[DiD_\ell | \mathbf{D} = \delta_{s,t}\right]$.

3.6. Results

3.6.1. Baseline results

Table 3.2 presents the average cumulative (total) effects of coca cultivation on school outcomes across different buffer sizes. Consistent with our identification strategy and theoretical expectations, school enrollment declines as coca cultivation increases around schools. Specifically, for every 1% increase in coca cultivated within a 1 *km* radius of a school, enrollment decreases by approximately 0.06 standard deviations and school dropouts increase by 0.13 standard deviations. On average, there is no significant effect on academic failure. Moreover, as the buffer radius increases, the average estimated effect appears to diminish in magnitude, suggesting that coca cultivation closer to schools has a more direct and substantial impact on its outcomes.

Table 3.2: Response of educational outcomes on Coca crops surrounding schools (2013-2019)

	1 km Buffer			5 km Buffer		
	Enrollment	Dropout	Failure	Enrollment	Dropout	Failure
Coca ln	-0.064***	0.133***	0.021	-0.023***	0.000	0.024
	(0.012)	(0.004)	(0.046)	(0.005)	(0.030)	(0.019)
Obs.	223,378	232,831	232,831	225,912	219,834	219,834
Switchers	6,324	5,997	5,997	7,974	7,651	7,561

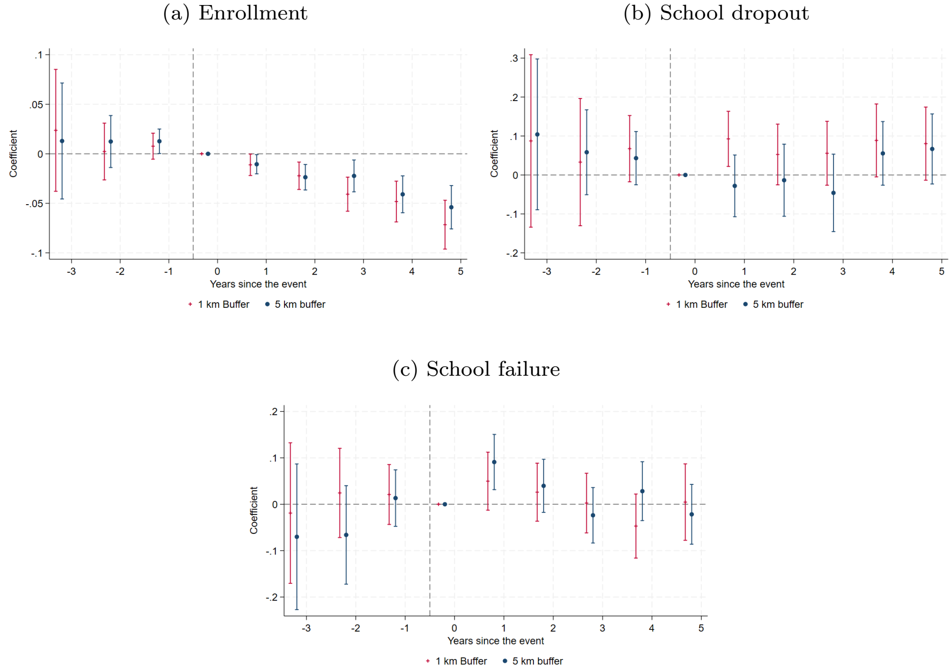
Dependent Variables are in standard deviation and independent in logarithms. Dropout and failure rates represent the proportion of enrolled students by school. We use school and year fixed effects. Errors are clustered at the school-level, and we control for regional linear trends. Each cell comes from a different estimation. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Furthermore, the estimation approach that we use allows us to capture how these outcomes evolve following the initial increase in coca cultivation intensity, rather than assuming an immediate or static response. Regarding dynamic effects, Figure 3.9 shows that the impact of coca cultivation surrounding schools occurs immediately following the initial treatment (*switch*). In the first years after exposure, enrollment decreases 0.01 standard deviation for every 1% increase in coca cultivation within a $1km$ radius, while dropout rates rise by approximately 0.1 standard deviations. Notably, although the rise in dropout rates stabilizes in subsequent periods, enrollment continues to decline steadily, reaching a reduction of 0.07 standard deviations five years after the initial increase in coca crop cultivation within a 1 km radius around each school. This persistent decline suggests that the effect is not solely driven by students leaving school mid-year, but also by a reduced probability of enrollment in subsequent academic cycles.

Although we do not find a statistically significant average effect of coca cultivation on academic failure rates, Figure Panel B in Figure 3.9 shows an increase in school failure of nearly 0.1 standard deviations for each 1% rise in coca cultivation within a $5km$ buffer around schools. This pattern may reflect several underlying dynamics; in particular, when coca expansion occurs farther from schools, students may face a trade-off between academic performance and participating in coca-related labor activities (Cancillería de Colombia, 2016; Defensoría del Pueblo de Colombia, 2020; Dirección de Antinarcóticos, 2014).

Finally, the null hypothesis of the Parallel Trends Assumption is that all placebo estimators are close to zero and not statistically significant. Panels A, B, and C in figure 3.9 show that the assumption holds. Importantly, Figure C1 in the Appendix illustrates that our estimator adequately accounts for treatment heterogeneity and contamination, while the standard TWFE estimator fails to do so. In fact, the TWFE approach can yield misleading or counterintuitive results, as observed in the case of academic failure rates.

Figure 3.9: Dynamic effects of coca cultivation on enrollment



Dependent Variables are in standard deviation and independent in logarithms. Dropout and failure rates represent the proportion of enrolled students by school. We use school and year fixed effects. Errors are clustered at the school level. We control for regional linear trends. Each estimate comes from a different specification. We use 95% confidence intervals.

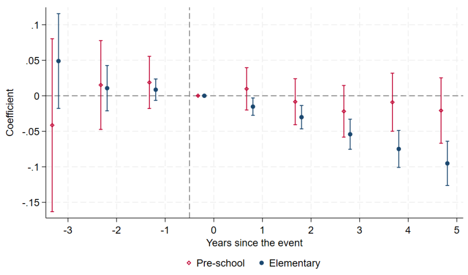
3.6.2. Effects by school level

To further examine the heterogeneity of these effects, we assess whether the impacts vary by level of schooling. As hypothesized, Panel A in Figure 3.10 shows that enrollment and dropout responses are primarily driven by elementary school students, who experience declines of approximately 0.1 standard deviations for each 1% increase in coca cultivation within a 1 *km* radius of their school; the effects persist even five years after the initial expansion. Additionally, elementary students experience a slight but significant increase in dropouts during the first year following the shock (Panel C). Interestingly, preschoolers, typically under five years old and highly dependent on their caregivers, display a delayed increase in dropout rates four to five years after the initial rise in coca cultivation. Regarding previous discussions, this pattern points out that the effects observed at preschool levels may be linked to caregiver-driven regional migration in search of new employment opportunities following the expansion of coca crops. Lastly, we found that elementary school students are those who are more likely to academically fail if coca crop shocks occur within a 5 *km* radius around their school.

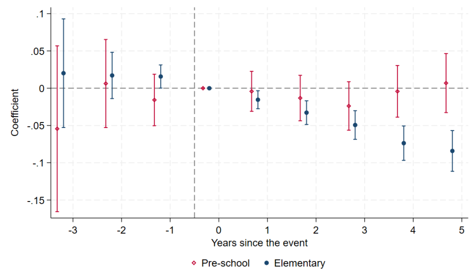
Additionally, we examine whether these responses differ by gender. Figure 3.11 depicts that, overall, we do not find systematic patterns favoring or disadvantaging either gender. However, we observe that girls experience larger declines in enrollment, persisting even four years after the initial coca shock within a 1 *km* radius of their school.

Figure 3.10: Dynamic effects of coca cultivation on school outcomes by education level (2013-2019)

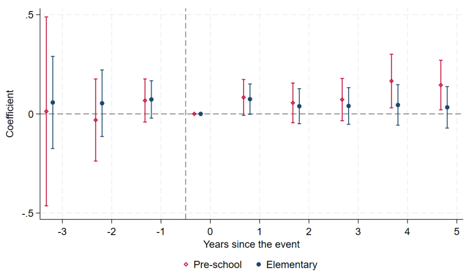
(a) Enrollment (1 km)



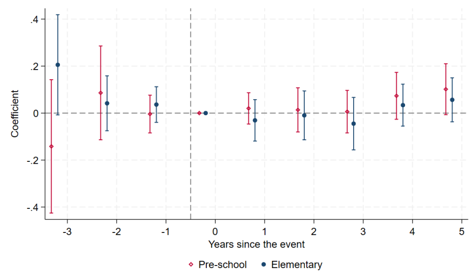
(b) Enrollment (5 km)



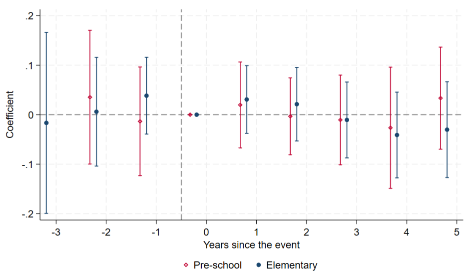
(c) School dropout(1km)



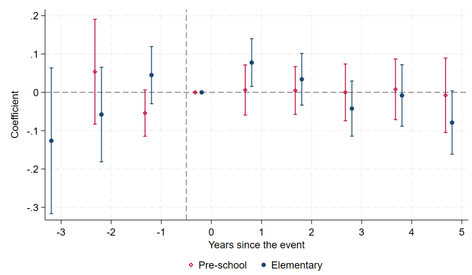
(d) School dropout (5km)



(e) School failure (1 km)

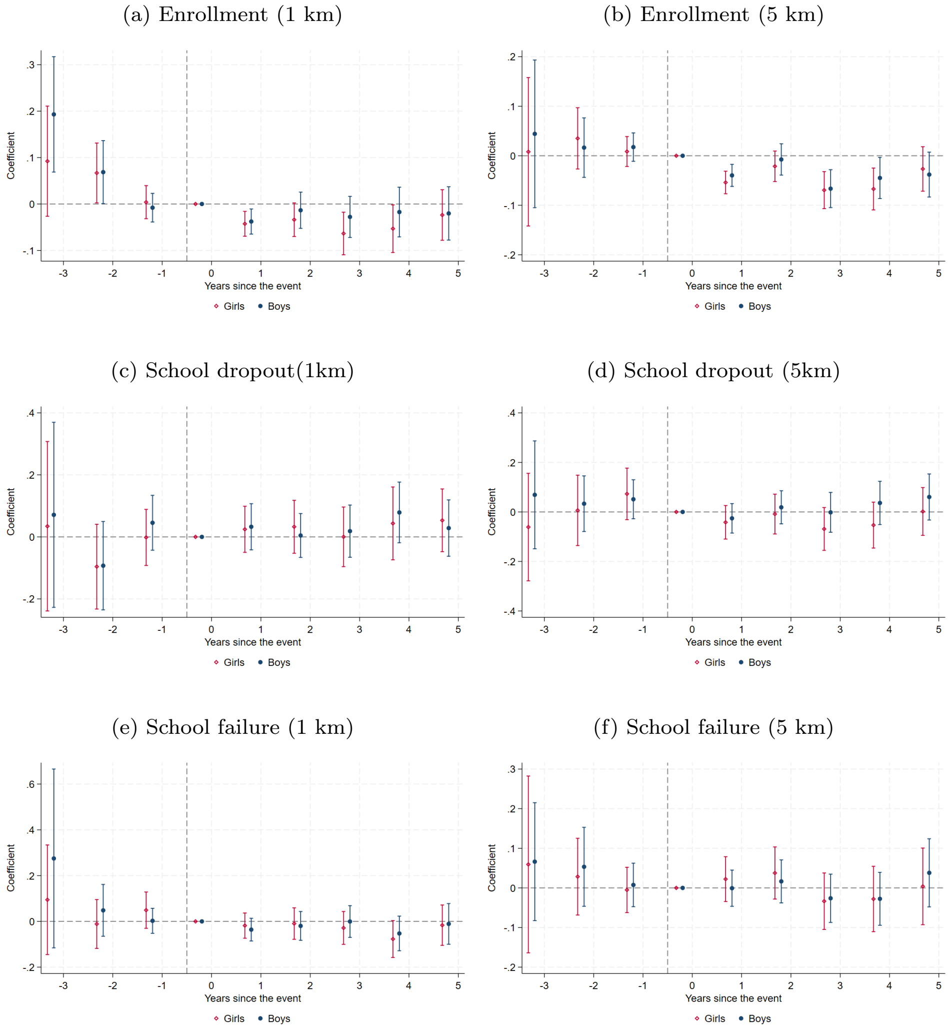


(f) School failure (5 km)



Dependent Variables are in standard deviation and independent in logarithms. Dropout and failure rates represent the proportion of enrolled students by school. We use school and year fixed effects. Errors are clustered at the school level. We control for regional linear trends. Each estimate comes from a different specification. We use 95% confidence intervals.

Figure 3.11: Dynamic effects of coca cultivation on school outcomes by gender (2013-2019)



Dependent Variables are in standard deviation and independent in logarithms. Dropout and failure rates represent the proportion of enrolled students by school. We use school and year fixed effects. Errors are clustered at the school level. We control for regional linear trends. Each estimate comes from a different specification. We use 95% confidence intervals.

3.6.3. Robustness checks

As a robustness check, we re-estimate the model by replacing the intensive margin of coca cultivation with an extensive margin indicator, defined as the number of coca cultivation grids contained within each buffer around schools. Table 3.3 shows that the estimates remain consistent with the baseline results, suggesting that the main findings are not sensitive to the choice of treatment measure, as it is the intensity itself.

Table 3.3: Response of educational outcomes on Coca grids surrounding schools (2013-2019)

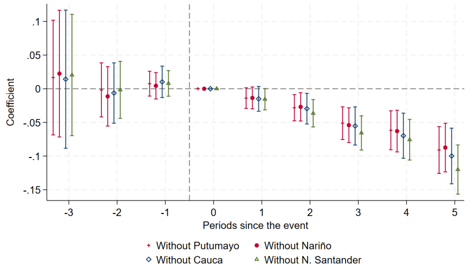
	1 km Buffer			5 km Buffer		
	Enrollment	Dropout	Failure	Enrollment	Dropout	Failure
Coca ha	-0.074***	0.154***	0.024	-0.024***	0.000	0.024
	(0.014)	(0.064)	(0.053)	(0.005)	(0.031)	(0.020)
Obs.	239,378	232,831	232,831	225,914	219,836	219,836
Switchers	6,345	5,997	5,997	7,975	7,562	7,562

Dependent Variables are in standard deviation and independent in logarithms. Dropout and failure rates represent the proportion of enrolled students by school. We use school and year fixed effects. Errors are clustered at the school-level, and we control for regional linear trends. Each cell comes from a different estimation. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

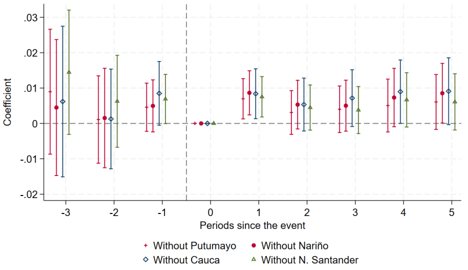
To assess the robustness of our estimates, we also conduct a subsample analysis excluding departments historically characterized by high levels of coca cultivation. This exercise helps to rule out the possibility that our results are driven by structural conditions specific to regions with persistent coca presence. Specifically, we re-estimate the model after excluding four departments, Putumayo, Nariño, Cauca, and Norte de Santander, which together accounted for a significant 73% of the share of national coca production in 2014 (UNODC, 2015). The results remain consistent with our main findings, suggesting that the observed effects are not solely concentrated in these high-exposure regions.

Figure 3.12: Dynamic effects of coca cultivation 1 km around schools on educational outcomes without high coca crops rates departments

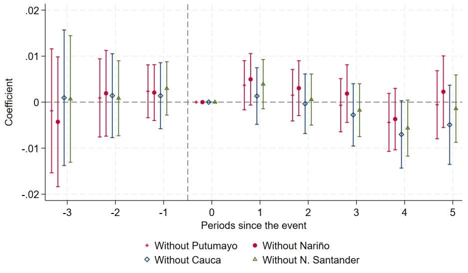
(a) Enrollment



(b) Dropouts



(c) Failure



Dependent Variables are in standard deviation and independent in logarithms. Dropout and failure rates represent the proportion of enrolled students by school. We use school and year fixed effects. Errors are clustered at the school level. We control for regional linear trends. Each estimate comes from a different specification. We use 95% confidence intervals.

3.7. Conclusions

Our findings provide robust evidence that exposure to coca cultivation and its surrounding dynamics negatively affects educational outcomes, particularly at the elementary school level. By exploiting temporal variation in the intensity of coca cultivation around schools, our identification strategy moves beyond a simple binary exposure framework. Unlike a sharp-event specification estimated via TWFE, our dynamic difference-in-differences approach with continuous treatment allows us to capture the heterogeneous and evolving nature of coca cultivation effects. The results suggest that the adverse impacts on enrollment, dropout, and academic performance are not merely a function of the presence of coca crops, but are closely linked to the scale and persistence of their expansion near schools. Moreover, thanks to the granularity of our observational unit at the school level, we find that the negative effect on enrollment is concentrated among elementary school students, contrasting with the municipality-level findings of Angulo (2024), who reported no such effect.

Drawing on documented reports and previous studies, we conclude that students living in areas affected by coca cultivation are involved in complex social and economic environments that delay their educational attainment and perpetuate intergenerational cycles of poverty. The trade-off they face between participating in coca-related labor and pursuing formal education, particularly in contexts where basic needs remain unmet, translates into higher dropout rates and reduced school enrollment in subsequent years. Moreover, when coca crops are located farther from schools, even students who attempt to remain enrolled may experience declines in academic performance due to the increased strain of mobility and exposure to adverse external conditions.

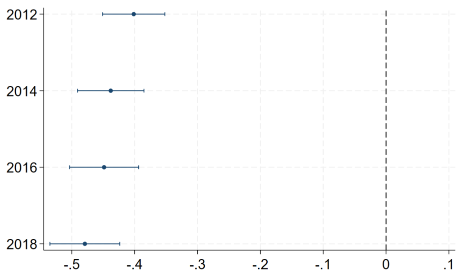
Finally, we show that the effects are not solely driven by regions with the highest share of coca cultivation, which reinforces the strengths of our identification strategy. By leveraging variation in the intensity of treatment and its temporal changes at the unit level, rather than relying on a single sharp treatment event.

3.A Appendix

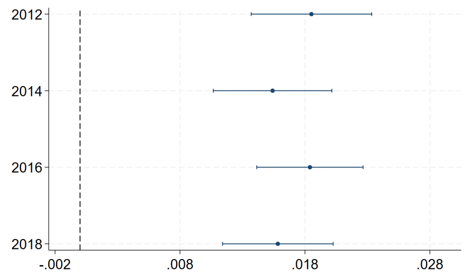
3.A.1. Descriptive statistics

Figure A1: Mean differences by coca cultivation exposure - Comparable sample at 1 km Buffer

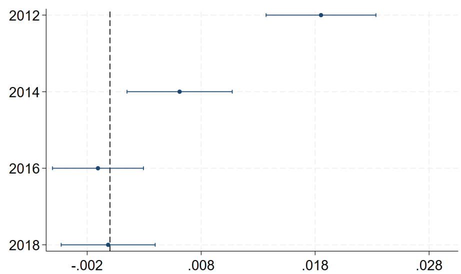
(a) School enrollment



(b) School dropout rate



(c) School failure rate



Variables are in standard deviations. Figures report mean differences between no-coca-influenced and coca-influenced schools. We use 95% confidence intervals.

3.A.2. de Chaisemartin and D'Haultfœuille, 2023 estimators dynamics (DiD_ℓ)

Table B1: TWFE Weights

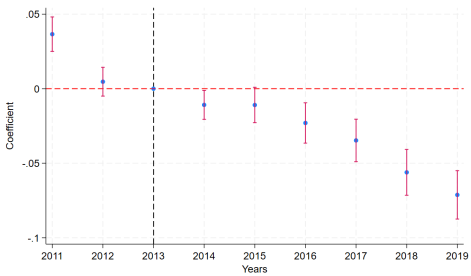
Treatment variable (ln)	# ATTs	Weights
Panel A. Coca (Buffer 1 *km*)		
Positive weights	898	1.5840
Negative weights	762	-0.5480
Panel B. Coca (Buffer 5 *km*)		
Positive weights	1,522	1.7615
Negative weights	1,118	-0.7615

Estimates of TWFE weights where made with school enrollment as a dependent variable.

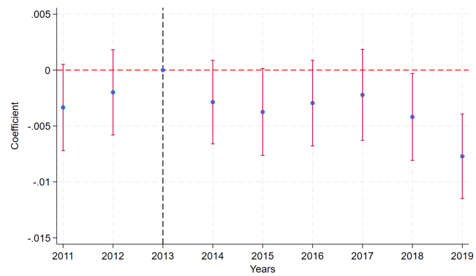
3.A.3. Additional estimates

Figure C1: TWFE estimator

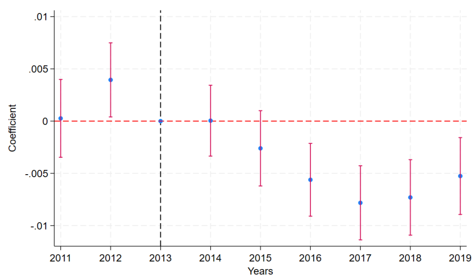
(a) Enrollment



(b) Dropout



(c) Failure



Dependant variables are in standard deviations, and independent variables are in logarithms. Both school dropout and failure are a proportion of the enrolled students at a school. We use school and year fixed effects. Errors are clustered at the school level. We control for regional linear trends.

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