Migration, Market Power, and Firms*

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March 26, 2026

Abstract

This paper studies the wage effects of migration in a setting where firms possess market power in both labor and product markets. Exploiting the Venezuelan exodus to Colombia as a large and exogenous migration shock, and using firm-level production function estimates, I show that migration increased firm employment, output, and the marginal productivity of labor in the Colombian manufacturing sector, yet had no effect on average wages. I demonstrate that this pattern cannot be reconciled with competitive models and instead reflects endogenous adjustments in firms' labor and product market power. Migration increased firms' wage markdowns by reducing the value of self-employment—an outside option for manufacturing workers—while simultaneously shifting local demand toward more price-sensitive consumers and reducing price markups, muting the pass-through of productivity gains into wages. To rationalize these findings, I develop a general equilibrium model with imperfect competition in both labor and product markets, in which wages depend not only on the marginal product of labor but also on endogenous wage markdowns and price markups. Workers self-select between wage employment and self-employment, making the latter a key outside option for wage workers and a channel through which migration affects labor market power. At the same time, migrant inflows alter the composition and elasticity of product demand. Together, the empirical and theoretical results highlight the importance of jointly accounting for labor and product market power when interpreting the wage effects of migration.

JEL Classification: F22, J21, J61, J42, L10, O17
Keywords: Market Power, Migration, Firms, Development.

*I am grateful for the guidance and support of Nancy Chau and Philipp Kircher. I also thank Julieta Caunedo, Justin Bloesch, Sampreet Goraya, Federico Mandelman, Salvador Navarro, Ezra Oberfield, Giovanni Peri, Vaios Triantafyllou, as well as participants in Cornell University's Labor Work in Progress Seminar, SOLE 2025, the 18th AFD-World Bank Migration and Development Conference, the 4th Workshop on the Macroeconomic Implications of Migration, and the Global Migration Center - University of California, Davis for their helpful comments and suggestions.

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1 Introduction

The effect of migration on wages remains a contested topic in both public policy debates and academic research. A large body of economic evidence suggests that average wage effects are close to zero, with at most small negative impacts in some contexts (Longhi et al., 2005; Peri, 2014; Aubry et al., 2026). The economic literature has proposed several mechanisms to rationalize this apparent absence of wage effects, including differences between short- and long-run adjustments, complementarities between migrant and native workers, capital adjustment dynamics, pure scale effects driven by increased demand, and task-based reallocation within firms (Peri and Sparber, 2009; Ottaviano and Peri, 2012; Peri, 2012; Olney, 2015; Beerli et al., 2021; Galaasen et al., 2025). These mechanisms are often invoked to argue that migration-induced productivity gains may offset downward pressure on wages, thereby explaining the muted average wage responses observed in the data.

Most existing analyses, however, rely on a standard competitive supply and demand framework and conceptualize migration primarily as a labor supply shock to the host economy, implicitly assuming perfectly competitive labor and product markets. Under this benchmark, wages are assumed to fully reflect marginal productivity, so the absence of wage effects is typically interpreted as evidence that productivity gains exactly compensate for increased labor supply.

Yet this interpretation is incomplete if firms possess market power. A growing body of research documents that both labor and product markets are often far from perfectly competitive, underscoring the importance of incorporating market power into the analysis of migration impacts (Van Reenen, 2024; Deb et al., 2024). On the labor market side, recent work highlights the pervasiveness of firm-level labor market power across both developed and developing economies (Manning, 2011; Yeh et al., 2022; Berger et al., 2022; Amodio et al., 2024; Estefan et al., 2024). In such environments, changes in productivity may not be fully passed through to workers, and firm wage-setting power—often overlooked in migration studies—can play a central role in shaping observed wage responses to migrant inflows.

At the same time, migration also affects the demand side of the host economy. Beyond increasing aggregate demand for locally produced goods—and thereby labor demand and wages in competitive settings (Cengiz and Tekgüç, 2022; Galaasen et al., 2025)—migration can alter the income composition of local demand. By shifting the distribution of consumers toward lower-income households, who tend to be more sensitive to price changes (Sangani, 2022), migrant inflows may weaken firms' ability to set prices above marginal cost, reducing product market power and, in turn, influencing firms' optimal wage-setting decisions. For these reasons, understanding the wage effects of migration requires a framework that jointly accounts for labor and product market power.

In this paper, I argue that the absence of wage effects following migration cannot be fully understood within a competitive framework. I show that even when migration increases firm-level productivity—a mechanism frequently invoked to explain muted wage responses—wages may remain unchanged once labor and product market power are taken into account. I study the impact of a large migration shock within a non-competitive framework in which firms set both wages and prices, so that wages depend not only on the marginal productivity of labor but also on wage

markdowns and price markups. In addition, I examine medium-run outcomes to explore how these adjustments affect firm profitability and entry.

I focus on the influx of Venezuelan migrants into Colombia between 2012 and 2020. Amid Venezuela's economic and social turmoil, approximately 2.5 million Venezuelans migrated to Colombia. Exploiting geographic and temporal variation in migrant inflows, I study how this large shock affected the Colombian manufacturing sector. To do so, I estimate firm-level production functions using proxy variable approaches from the literature (Ackerberg et al., 2015; Gandhi et al., 2020). This allows me to recover the marginal productivity of inputs and to measure firm market power in both labor and product markets using methodologies developed by De Loecker and Warzynski (2012) and Yeh et al. (2022). I document substantial labor and product market power among manufacturing firms, comparable to estimates found in both developed and developing economies (Yeh et al., 2022; Amodio et al., 2024; Estefan et al., 2024).

When estimating the impact of the migration shock on firm outcomes, I find three main results. First, the migration shock increased both employment and output (measured in quantities) in the Colombian manufacturing sector. Second, because migrant workers employed in manufacturing were relatively high-skilled, their presence raised firm-level marginal productivity of labor. Third, despite these productivity improvements, average wages paid by firms did not increase.

I interpret this pattern within a non-competitive framework in which firms face an upward-sloping labor supply curve and a downward-sloping product demand curve. In this setting, productivity gains do not necessarily translate into higher wages if firms adjust wage markdowns and price markups. I provide evidence consistent with this mechanism. On the labor market side, the Venezuelan exodus increased firms' labor market power by raising wage markdowns. I argue that this increase was driven by a decline in the value of self-employment, which serves as an outside option for manufacturing wage workers (Amodio et al., 2025). As migrants concentrated in self-employment—an easily accessible and often precarious form of work in developing countries such as Colombia, particularly in the absence of formal work documentation—the value of this outside option declined, strengthening manufacturing firms' labor market power and reducing the pass-through of productivity gains into wages.

On the product market side, because migrants tend to have lower incomes and higher price sensitivity than native consumers, the inflow shifted the composition of local demand and reduced firms' price markups. Together with the increase in labor productivity, this reduction in markups offset the downward pressure on wages generated by the rise in firms' labor market power, which, in the absence of both product market power and productivity gains, would have led to wage declines. These forces allowed firms to capture productivity gains without increasing labor costs, thereby raising profits and stimulating firm entry in the years following the exodus.

To interpret these empirical patterns, I develop a tractable general equilibrium model with imperfect competition in both labor and product markets. Firms set wages in the presence of monopsonistic labor market power and set prices under downward-sloping demand, so that equilibrium wages depend not only on the marginal product of labor but also on endogenous wage markdowns and price markups. The model features heterogeneous native and migrant workers who choose between

wage employment and self-employment, which provides an outside option that disciplines firms' wage-setting behavior. On the demand side, native and migrant households differ in their elasticities of substitution across varieties and across sectors, allowing migration to shift the composition of local demand toward more price-sensitive consumers and thereby affect firms' optimal markups.

The model links these elements to the empirical mechanisms highlighted in the paper. A migrant inflow can reduce the value of self-employment by increasing competition in that sector, thereby lowering its attractiveness as an outside option and raising firms' wage markdowns, particularly for native workers (Amodio et al., 2025). At the same time, by expanding the mass of migrant consumers—who are assumed to be more price sensitive due to their substantially lower income—the shock increases the demand weight placed on higher-elasticity consumers. This raises the effective demand elasticity faced by firms and reduces equilibrium markups.

In addition, the model incorporates a formal–informal hiring margin, in which firms trade off payroll taxes against convex expected costs of informal employment that differ between migrants and natives. This intensive margin of informality within firms—similar to that in Ulyssea (2018)—provides a mechanism through which firms can capture the productivity gains of migrant workers who would otherwise be excluded from formal manufacturing employment due to the lack of legal authorization to work formally (e.g., work permits).

Together, the model delivers a unified framework in which migration can raise productivity while leaving wages largely unchanged, as endogenous adjustments in wage markdowns and price markups occur simultaneously, with implications for profits, entry, and welfare.

Related Literature. This paper contributes to several strands of the economic literature. First, it contributes to the literature on the demand effects of migration in host economies. Previous studies examine how migration affects demand, production decisions, or specific markets such as housing, typically within competitive product market frameworks (Saiz, 2003, 2007; Kerr and Kerr, 2011; Gonzalez and Ortega, 2013; Olney, 2015; Howard, 2020; Cengiz and Tekgüç, 2022; Peri et al., 2022; McCully et al., 2024; Galaasen et al., 2025). The closest papers to this one are Olney (2015) and Galaasen et al. (2025), which emphasize consumption-driven labor demand effects. This paper goes beyond these mechanisms by showing that when firms possess product market power, migration can affect wages not only through a pure scale effect—where higher goods demand raises labor demand and wages—but also through a compositional effect operating via changes in demand elasticities and firms' ability to set price markups.

Second, this paper contributes to the literature on the labor market effects of migration under imperfect competition (Naidu et al., 2016; Amior and Manning, 2020; Amior and Stuhler, 2022; Elias et al., 2024). While most studies of migration rely on competitive labor market assumptions (see, e.g., Ottaviano and Peri, 2012; Borjas, 2014; Card and Peri, 2016; Dustmann et al., 2016), Amior and Manning (2020) provides an early conceptual framework for how migration may affect labor market power. I extend this literature in three ways. First, I jointly analyze wage markdowns and price markups as channels through which migration affects wages. Second, I directly estimate firm-level labor market power using production-function methods. Third, I propose an additional mechanism, self-employment, through which migration can affect labor market power, particularly in developing

countries where self-employment constitutes a key outside option for wage workers. In this setting, migrants' disproportionate concentration in self-employment reduces its value as an outside option, thereby increasing firms' labor market power and amplifying wage markdowns.

Third, this paper contributes to the growing literature on labor market power in developing countries (Yeh et al., 2022; Amodio and De Roux, 2024; Amodio et al., 2024). While much of the existing evidence focuses on developed economies (Yeh et al., 2022; Berger et al., 2022; Azar et al., 2023), I identify migration as a key force shaping labor market power in developing countries. Closely related is Amodio et al. (2025), who studies the role of self-employment in Peru; I extend this framework by showing how migration affects the value of self-employment and, in turn, firm labor market power.

Finally, this paper contributes to the recent literature highlighting the relevance of firms' *double market power*, defined as the simultaneous exercise of market power in both labor and product markets (MacKenzie, 2021; Rubens, 2023; Kroft et al., 2025). As shown by Kroft et al. (2025), when firms possess *double market power*, market power in one market attenuates the degree of market power exercised in the other. Building on this insight, I show that migration affects both labor and product market power in the Colombian manufacturing sector, and that these effects partially offset each other. As a result, analyses that ignore either margin would lead to misleading conclusions about the wage effects of migration.

The paper is organized as follows. Section 2 provides background on the Venezuelan exodus into Colombia. Section 3 describes the data and presents descriptive statistics. Section 4 outlines the conceptual framework. Section 5 details the estimation of firm-level variables and the empirical strategy. Section 6 presents the main results. Section 7 discusses the main mechanisms affecting firms' labor and product market power. Section 8 examines the medium-run impacts of the migration exodus, and Section 9 presents robustness checks. Section 10 develops a general equilibrium model that rationalizes the main empirical findings through endogenous wage markdowns and price markups. Finally, Section 12 concludes.

2 Context: The Venezuelan Exodus

Since 2013, when Nicolás Maduro assumed leadership of the Chavismo regime in Venezuela, the country has experienced a profound economic and social collapse. According to official statistics from international organizations, Venezuelan GDP contracted by approximately 62% between 2013 and 2019, while annual inflation exceeded 100% from 2015 onward and reached nearly 180,000% in 2018 (ECLAC, 2019; Bonilla-Mejía et al., 2020). These macroeconomic shocks, combined with severe shortages of food and medicine, widespread human rights violations, political persecution, and a sharp decline in public revenues following the collapse of international oil prices—the country's main export—triggered an unprecedented wave of forced migration in the subsequent years (United Nations, 2019; Caruso et al., 2021; Peñaloza-Pacheco, 2022; Rozo and Vargas, 2021; UNHCR, 2022).

According to UNHCR (2022), by 2022 approximately 5.5 million Venezuelans had left the coun-

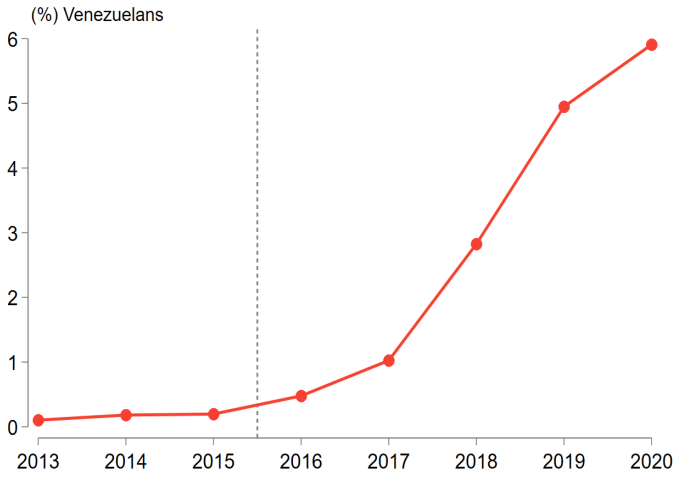
try and resettled abroad, primarily within Latin America. This figure represents nearly 20% of Venezuela's total population, based on the most recent national census conducted in 2011. Colombia, which shares a long and porous border with Venezuela, has been the principal destination during this mass exodus. Between 2016 and 2022, more than 2.5 million Venezuelans settled in Colombia in search of refuge and improved living conditions.

Although economic and social conditions in Venezuela had begun deteriorating prior to 2016, the large-scale inflow of migrants into Colombia accelerated sharply starting in August 2016. This timing reflects a political crisis between the Colombian and Venezuelan governments, during which the bilateral border was fully closed for nearly a year, from 2015 to 2016 (Peñaloza-Pacheco, 2022). Following prolonged negotiations, the reopening of the border triggered a rapid and massive influx of Venezuelan migrants into Colombia (see Figure 1).

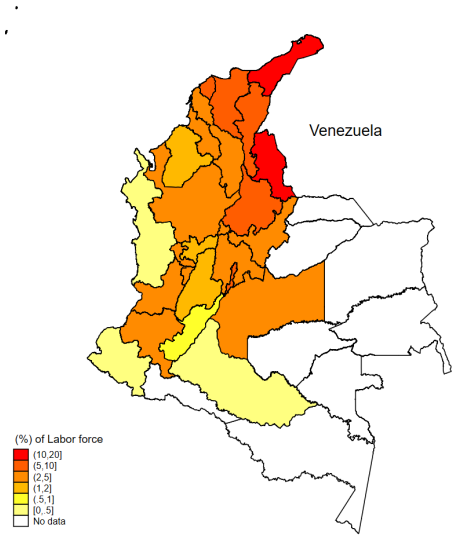
As shown in Panel A of Figure 1, migrant inflows increased rapidly over the 2016–2020 period, reaching nearly 6% of Colombia's total population by 2020. The geographic distribution of Venezuelan migrants exhibits pronounced spatial concentration in regions close to the Colombian–Venezuelan border. Panel B of Figure 1 shows that by 2019 migrants were disproportionately located in border departments. This pattern is consistent with the forced nature of the exodus: following the reopening of the border in 2016, many migrants entered Colombia on foot or via ground transportation, making nearby regions the most likely locations for initial settlement. This spatial concentration plays a central role in the empirical strategy, as it generates substantial heterogeneity in migrant exposure across local labor markets.

Figure 1: The Venezuelan Exodus in Colombia

(a) Percentage of Venezuelans in Colombia, 2013-2020



(b) Distribution of Venezuelans, 2019



Notes: Venezuelan immigrants are defined as individuals born in Venezuela. The percentage of Venezuelans in Panel (a) was calculated relative to the number of Colombians in 2015. The number of immigrants in Panel (b) was normalized by the working-age population of each department in 2012. Departments with no data in the figures primarily consist of regions in the Amazon characterized by low population density and small main cities where data is unavailable. According to the latest available census in Colombia (2018), the population in these departments accounts for less than 3% of the total population in Colombia. Survey weights are applied to calculate the shares by department. Source: Own elaboration based on GEIH data from DANE.

Consistent with this geographic pattern, calculations based on the Colombian GEIH reveal large differences in migrant exposure across regions. In major urban labor markets such as Bogotá and Antioquia, Venezuelans represented approximately 2.3% and 1.3% of the local labor force in 2019, respectively. In contrast, in border departments such as La Guajira and Norte de Santander, this share ranged between roughly 10% and 20%.

Finally, due to the forced nature of Venezuelan displacement, migrants have faced particularly adverse labor market conditions in Colombia. Despite the implementation of a large-scale amnesty program in 2018, which issued successive waves of temporary work permits, Venezuelan migrants continue to experience low wages, limited access to formal contracts, and restricted opportunities to work in occupations aligned with their skills (Bahar et al., 2021; Ibáñez et al., 2025).

3 Data and Descriptive Statistics

To analyze the impact of the Venezuelan exodus on firm outcomes I work with four main datasets. **Colombian Annual Manufacturing Survey (2012-2020).** The first source of data is the Colombian Annual Manufacturing Survey (EAM, by its acronym in Spanish) carried out by DANE. This dataset is a representative panel of the Colombian manufacturing sector that surveys manufacturing firms in Colombia with more than 10 employees or firms with fewer employees but with sales above a certain threshold. From the EAM, I have information regarding employment, wage bill, investment, capital, energy and raw materials demand, as well as intermediate consumption. Crucially, I have detailed quantity data on firms' inputs and outputs, which is essential for estimating firms' production functions.

Colombian 2018 Census. Secondly, to calculate the number of immigrants in each local labor market of Colombia, I use the 2018 Colombian Census carried out by the National Statistics Office (DANE, by its acronym in Spanish). The Census is the most accurate source of information regarding the number of Venezuelan immigrants in Colombia. I calculate, for each local labor market, the number of Venezuelans who entered the country during the 2015-2018 period.[1]

Great Integrated Household Survey (2013-2020). The third source of data used in this paper is the Colombian Household Survey (GEIH, by its acronym in Spanish). The GEIH is a nationally representative cross-sectional survey that inquires question related to sociodemographic characteristics of individuals, economic activity and labor market conditions of workers in the country. Also, since April 2013, it allows to identify migrants by country of origin over time. I will use the GEIH to characterize the labor market integration of Venezuelan and Colombian workers over time.

Encuesta Longitudinal Colombiana - ELCA (2013,2016). Fourth, I use data from the Colombian Longitudinal Survey (ELCA), conducted by Universidad de los Andes. The ELCA is a nationally representative household panel that follows individuals over time and records detailed information on employment status and sector of activity. Using the 2013 and 2016 waves, I exploit the panel

[1] The main limitation of the 2018 Census, is that it only captures the number of Venezuelans in Colombia up to 2018 and my analysis considers also 2019-2020. However, it is expected that in the last years of my period under study, migration trends for each local labor market reflect the patterns observed in the previous years.

structure of the survey to study transitions between employment categories and to document movements across manufacturing and non-manufacturing sectors.

Finally, I obtain some descriptive statistics on living conditions in Colombia of Venezuelans, from the Encuesta Pulso de la Migración (EPM) carried out by DANE since 2021.

3.1 Venezuelan Migrants in Colombia

This subsection documents the main characteristics and labor market integration of Venezuelan migrants in Colombia, and highlights the key features that motivate the structure of the empirical analysis and the theoretical framework developed in the paper.

Table 1 presents descriptive statistics comparing Venezuelan migrants in 2019—at the end of the analysis period—with Colombian natives in 2015, the baseline period prior to the reopening of the border. Panel A reports statistics for individuals aged 18–65. Venezuelans are slightly more likely to be male, are younger on average, and have more years of education than Colombians. Decomposing the population by educational attainment reveals that Colombians are substantially more likely to have only primary education, whereas Venezuelans are more represented among individuals with secondary education or some post-secondary schooling. These patterns are consistent with standard migrant self-selection, whereby migrants are disproportionately of working age and relatively well educated. As a result, the Venezuelan exodus represented a sizable increase in the supply of workers who are at least as qualified as native workers in Colombia. Despite this, Venezuelans are less likely to be employed overall and, conditional on labor force participation, face higher unemployment rates than Colombians.

The second part of Panel A reports per capita income distributions for Colombians and Venezuelans. On average, Venezuelans have approximately 20% lower per capita income than Colombians, and their income distribution is markedly left-skewed. Moreover, within each nationality-specific income quartile, Venezuelans earn significantly less than Colombians. This income gap is central to the analysis because it shifts the composition of local demand toward more price-sensitive consumers, limiting firms' ability to set prices above marginal cost. I elaborate on this demand-side mechanism and its implications for price markups in Sections 4 and 10.

To characterize labor market integration more precisely, I classify workers—both overall and within manufacturing—into four mutually exclusive categories: informal self-employment, formal self-employment, informal wage employment, and formal wage employment. This taxonomy reflects the extensive and intensive margins of informality emphasized in the development literature (Ulyssea, 2018). Self-employed workers operate independently, but a critical distinction exists between formal self-employment—typically associated with entrepreneurship and greater economic stability—and informal self-employment, which is substantially more precarious. Wage workers are employed in dependent relationships with firms; however, informality is also prevalent when workers are hired off the books by formally established firms.

Panel B of Table 1 reports labor market outcomes for employed individuals, both overall and within manufacturing. The educational patterns documented in Panel A carry over to the employed

population. Notably, within manufacturing, the share of Venezuelans with post-secondary education exceeds that of Colombians by a larger margin than in the overall workforce, consistent with higher barriers to entry in this sector. In terms of outcomes, Venezuelans earn significantly lower hourly wages and work more weekly hours than Colombians. Among all employed individuals, Venezuelans earn approximately 10% lower hourly wages and work 11% more hours per week. In manufacturing, these gaps widen to 13% lower hourly wages and 7% more weekly hours.

Several additional patterns emerge from the employment distribution. Overall, the share of self-employment is similar for Colombians (51%) and Venezuelans (49%). However, the composition differs sharply by nationality. Roughly 20% of Colombian self-employed workers are formal self-employed, whereas nearly all Venezuelan self-employed workers are informal. This contrast is even more pronounced within manufacturing. Given that formal self-employment represents a small and stable share of employment and is largely unaffected by the migration shock, the remainder of the paper focuses exclusively on informal self-employment when referring to self-employed workers.

Among wage workers, who account for roughly half of employed individuals in both groups, informality rates differ starkly by nationality. Approximately 35% of Colombian wage workers are informally employed, compared to nearly 80% of Venezuelan wage workers. In manufacturing, informal employment accounts for about 25% of Colombian wage workers but almost 75% of Venezuelans. These patterns reflect the institutional and legal constraints migrants faced upon arrival, as many lacked the documentation required for formal employment. At the same time, they illustrate a defining feature of informality in developing economies: the intensive margin of informality, whereby formally established firms employ a substantial share of their workforce informally.

Finally, complementary evidence from the Encuesta Pulso de la Migración (EPM) reinforces the relevance of local labor market exposure. According to the EPM, nearly 92 percent of Venezuelans report migrating to improve their economic conditions, and approximately 96 percent plan to remain in Colombia. Despite relatively high educational attainment, only 7.1 percent of migrants with post-secondary education have been able to validate their degrees. Moreover, approximately 95 percent of Venezuelans remained in the same municipality between 2016 and 2019, a rate comparable to that of Colombian natives, indicating limited geographic mobility during the period of analysis.

Table 1: Descriptive Statistics of Venezuelan Migrants, 2013-2019

	Colombians	Venezuelans	Difference	p-value
Panel A: Socio-demographic characteristics (overall)				
Male	0.58	0.60	0.01	0.04
Age	37.2	31.0	-6.19	0.00
Years of Education	9.72	10.8	1.03	0.00
Primary education	0.42	0.32	-0.10	0.00
Secondary education	0.45	0.54	-0.09	0.00
Post-secondary education	0.13	0.14	0.01	0.04
Employment	0.90	0.84	-0.05	0.00
Unemployment	0.10	0.16	0.05	0.00
Average Per capita income (in logs)				
Overall	12.88	12.68	-0.20	0.00
1st quartile	11.77	11.57	-0.20	0.00
2nd quartile	12.68	12.38	-0.30	0.00
3rd quartile	13.22	12.87	-0.35	0.00
4th quartile	14.11	13.63	-0.48	0.00
Panel B: Working individuals				
Overall				
Education				
Primary education	0.43	0.31	-0.12	0.00
Secondary education	0.44	0.54	0.10	0.00
Post-secondary education	0.13	0.15	0.02	0.02
Labor market variables				
Hourly wage (in logs)	8.15	8.06	-0.10	0.01
Weekly hours worked	3.74	3.85	0.11	0.00
Informal Self-employment	0.42	0.48	0.06	0.01
Formal Self-employment	0.09	0.01	-0.08	0.00
Informal Wage-employment	0.17	0.41	0.24	0.00
Formal Wage-employment	0.32	0.10	-0.22	0.00
Manufacturing Sector				
Education				
Primary education	0.37	0.27	-0.10	0.00
Secondary education	0.53	0.58	0.05	0.05
Post-secondary education	0.10	0.15	0.05	0.00
Labor market variables				
Hourly wage (in logs)	8.17	8.04	-0.13	0.00
Weekly hours worked	3.79	3.86	0.07	0.00
Informal Self-employment	0.31	0.39	0.07	0.02
Formal Self-employment	0.06	0.00	-0.06	0.00
Informal Wage-employment	0.16	0.45	0.29	0.00
Formal Wage-employment	0.47	0.16	-0.31	0.00

Notes. All statistics are computed for individuals aged 18–65. Statistics for Colombians are based on observations from the 2015 wave of the GEIH, while statistics for Venezuelans are based on observations from the 2019 wave. Primary education refers to individuals with less than completed secondary education. Secondary education refers to individuals who have completed secondary education but have not completed college. Post-secondary education refers to individuals with completed college education. Unemployment incidence is calculated among individuals in the labor force. Income per capita statistics report the average (log) per capita income of Colombians and Venezuelans within each nationality-specific income quartile. Standard errors for the difference-in-means p-values are clustered at the local labor market level. Source: Own elaboration based on GEIH data from DANE.

3.2 Transitions between Self-employment and wage-work

This subsection provides direct evidence on worker mobility between wage employment and self-employment, which motivates the definition of self-employment as an outside option in the theoretical framework developed to rationalize the empirical findings. Using the 2013-2016 panel structure of the Colombian Longitudinal Survey (ELCA) from Universidad de los Andes, Table 2 reports transitions across employment categories and between manufacturing and non-manufacturing activities. The first Overall row in Panel A shows the share of individuals who, conditional on being in a given employment category in 2013, switched to the other category by 2016. The estimates indicate that approximately 17.1% of Colombian workers who were wage workers in 2013 transitioned to self-employment in 2016. Conversely, about 22.7% of individuals who were self-employed in 2013 transitioned into wage employment by 2016.

The next four rows break down these transitions by formality status. As shown, most transitions from wage work to self-employment are driven by wage workers who move into informal self-employment. This pattern is expected, as formal self-employment typically corresponds to business ownership, which entails substantial entry barriers that wage workers are unlikely to meet regardless of their initial formality status. If anything, wage workers who are more likely to transition into formal self-employment are those who were previously formal and may have accumulated capital; however, this group remains very small (0.7%).

Turning to transitions from self-employment to wage work, two patterns emerge once formality is taken into account. First, the majority of these transitions originate from informal self-employment and lead either to informal or formal wage work, with transitions into informal wage employment being more common (13.3%). That is, informal self-employed individuals are more likely to enter wage employment informally rather than formally. Second, transitions from formal self-employment to wage work are rare; when they do occur, they tend to be transitions from formal self-employment to formal wage employment (0.3%).

Panels B and C of Table 2 report the same transitions conditional on the sector of origin, namely manufacturing or non-manufacturing. Focusing on transitions from wage work to self-employment, around 21.1% of manufacturing wage workers in 2013 became self-employed by 2016, compared to 16.2% of wage workers in non-manufacturing. Examining sectoral destinations reveals that manufacturing wage workers who switch to self-employment are more likely to do so in non-manufacturing activities (12.1%) than to remain in manufacturing as self-employed workers (9%). In contrast, among wage workers originating in non-manufacturing, virtually all individuals who transition to self-employment remain in non-manufacturing activities.

Turning to transitions from self-employment to wage work, approximately 15.3% of self-employed individuals in manufacturing transitioned into wage employment by 2016, compared to 23.9% of self-employed workers in non-manufacturing. Conditional on originating in manufacturing self-employment, individuals are slightly more likely to transition into manufacturing wage jobs (8.3%) than into non-manufacturing wage jobs (7%). By contrast, among individuals originating in non-manufacturing self-employment, nearly all those who transition into wage employment do so in

non-manufacturing activities (22.6%), with very few moving into manufacturing wage jobs (1.3%).

Table 2: Transitions between employment categories and economic sectors, 2013-2016

	Wage-work → Self-employment		Self-employment → Wage-work	
	Mean	SD	Mean	SD
Panel A: All sectors				
Overall	0.171	0.377	0.227	0.419
Informal to Formal	0.000	0.018	0.091	0.288
Informal to Informal	0.079	0.269	0.133	0.339
Formal to Formal	0.007	0.085	0.003	0.057
Formal to Informal	0.085	0.279	0.000	0.000
Panel B: Origin Manufacturing				
Overall	0.211	0.409	0.153	0.361
To Manufacturing sector	0.090	0.286	0.083	0.277
To Non-manufacturing sector	0.121	0.327	0.070	0.256
Panel C: Origin Non-manufacturing				
Overall	0.162	0.369	0.239	0.426
To Manufacturing sector	0.001	0.036	0.013	0.113
To Non-manufacturing sector	0.161	0.367	0.226	0.418

Notes. The first Overall row in Panel A reports the proportion of individuals who, conditional on working in a given employment category in 2013, switched to a different employment category by 2016, as indicated by the column headers. The next four rows decompose this proportion by informality status at the origin and destination. Panel B reports the same transitions conditional on individuals working in the manufacturing sector in 2013, while Panel C reports transitions conditional on individuals working in the non-manufacturing sector in 2013. Source: Own elaboration based on ELCA data from Universidad de los Andes.

Taken together, these patterns highlight two key facts. First, transitions across employment categories are common and frequently involve sectoral reallocation. Second, because nearly 60% of manufacturing wage workers who transition into self-employment move into non-manufacturing activities, self-employment outside manufacturing represents a central outside option for manufacturing wage workers. Accordingly, throughout the paper I define the self-employment outside option broadly, encompassing self-employment in all economic activities rather than restricting attention to manufacturing alone. This empirical evidence directly motivates the theoretical framework's treatment of self-employment as a common outside option that disciplines wage-setting in manufacturing.

3.3 Venezuelan Labor Supply Shock

In this subsection, I present descriptive evidence characterizing the labor supply shock induced by the Venezuelan exodus in the economy analyzed in this paper. The analysis focuses on manufacturing wage employment and self-employment, which are the main employment categories considered throughout the paper. To better capture the labor supply shock faced by firms in the estimation sample, manufacturing descriptives are further restricted to firms with more than 10 employees located in local labor markets covered by the EAM.

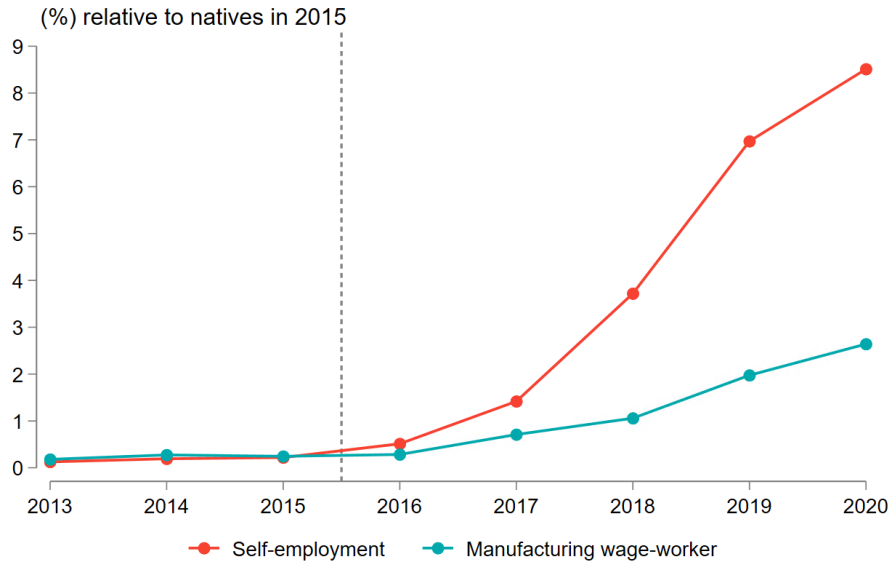
Figure 2 illustrates the magnitude and sectoral concentration of this shock by plotting the share

of Venezuelan workers in manufacturing wage employment and in total self-employment, relative to Colombians in 2015, the baseline period. Prior to 2016, Venezuelan presence in both categories was negligible. Following the onset of the exodus, the share of Venezuelans in self-employment increased sharply by approximately 9 percentage points, while their share in manufacturing wage employment rose by about 2 percentage points. Thus, although both sectors were affected, the labor supply shock was disproportionately concentrated in self-employment.

Because the increase in labor supply was substantially larger in self-employment than in manufacturing wage employment, output in self-employment may have expanded more rapidly relative to demand, intensifying competition and reducing the value of self-employment earnings. Since self-employment constitutes a key outside option for manufacturing wage workers, this decline may strengthen firms' labor market power—a mechanism developed in detail below.

Panel (a) of Figure A.1 further documents the heterogeneity of the labor supply shock by reporting the share of Venezuelans relative to Colombians in 2019 across 2-digit manufacturing industries in the EAM sample and across firm-size bins. The figure reveals substantial variation across economic activities: sectors related to clothing, furniture, and metal manufacturing experienced the largest inflows, while the chemical sector was the least affected. Panel (b) shows that the magnitude of the supply shock declines with firm size, indicating that Venezuelan employment in manufacturing was concentrated in smaller firms. This pattern is consistent with the fact that, during the period under study, most Venezuelans employed as manufacturing wage workers did so under informal arrangements, which are more prevalent among smaller firms.

Figure 2: Venezuelan Labor Supply Shock, 2013-2020



Notes: The figure reports the share of Venezuelans in self-employment (informal) and in manufacturing wage employment, relative to the corresponding shares for Colombians in 2015. Manufacturing wage employment is restricted to individuals working in firms with 10 or more employees and located in municipalities covered by the EAM. Source: Own elaboration based on GEIH data from DANE.

3.4 The Manufacturing Sector in Colombia

According to official statistics from DANE, by 2015 the manufacturing sector accounted for approximately 12% of total employment in Colombia, making it the third largest sector in terms of employment, after commerce and agriculture. Table 3 presents descriptive statistics for manufacturing firms in the sample.

On average, firms in the sample employ approximately 65 workers, of whom about 63% are white-collar employees. Labor costs represent a substantial share of firm revenues: the total wage bill accounts for roughly 25% of sales. Consistent with skill premia in the labor market, the average annual wage paid to white-collar workers is approximately 2.4 times higher than that paid to blue-collar workers.

Table 3: Descriptive Statistics of Manufacturing Firms, 2013-2019

	Mean	Median	S.D.	Min	Max
Employment	65.38	40	65.56	10	482
White-collar workers	24.28	14	28.86	1	238
Blue-collar workers	41.10	26	42.66	3	341
Wage bill / Sales	0.25	0.24	0.11	0.04	0.94
Capital (in COP 100,000)	38.62	12.26	85.13	0.36	1300
Annual Wage (in COP 100,000)	234.38	215.28	88.61	51.52	1,091.29
Annual Wage Blue-Collars (in COP 100,000)	181.16	168.83	55.27	49.13	1,023.15
Annual Wage White-Collars (in COP 100,000)	434.96	329.85	368.52	19.44	7,379.92
Sales (in COP 1,000,000)	7,280.57	3,360.62	11,300.00	311.79	128,000.0

Notes. Own elaboration based on EAM data from DANE.

4 Theoretical Framework: Main Intuitions

This section provides a simple conceptual framework to illustrate the mechanisms through which migration can affect wages in a non-competitive environment. The analysis in this section is intended to provide intuition that helps rationalize the empirical results presented in the paper. In Section **??**, I then formalize these insights in a tractable general equilibrium model.

Consider a simple economy in which firms face a downward-sloping product demand curve and an upward-sloping labor supply curve. Firms use labor (ℓ) as their only input. The firm's profit function is given by:

$$\Pi = p(q(\ell))q(\ell) - w(\ell)\ell \tag{1}$$

where $q(\ell)$ denotes output as a function of labor, $p(.)$ is the inverse demand function, and $w(.)$ is the wage schedule reflecting firms' wage-setting power. The first-order condition with respect to labor is:

$$\frac{\partial p}{\partial q}\frac{\partial q}{\partial \ell}q + p\frac{\partial q}{\partial \ell} = \frac{\partial w}{\partial \ell}\ell + w \tag{2}$$

Rearranging this expression yields:

$$p \times MPL\left(\frac{\varepsilon - 1}{\varepsilon}\right) = w\left(\frac{1+\eta}{\eta}\right) \tag{3}$$

Where ε denotes the elasticity of product demand faced by the firm and η denotes the elasticity of labor supply. Defining the product market markup $\mu \equiv \varepsilon/(\varepsilon - 1)$ and the wage markdown $\nu \equiv (1+\eta)/\eta$, wages can be expressed as:

$$w = \frac{p \times MPL}{\mu\nu} \tag{4}$$

Taking logs yields:

$$log(w) = log(MPL) - log(\mu) - log(\nu) + log(p) \tag{5}$$

This expression highlights that, in a non-competitive setting, wages depend not only on the marginal productivity of labor but also on firms' market power in both product and labor markets. Consequently, the effect of migration on wages can operate through three distinct channels: changes in labor productivity, changes in labor market power (wage markdowns), and changes in product market power (price markups). The following subsections discuss each channel separately.

4.1 Labor Market Power: Wage Markdowns

The labor market power of firms can be affected by migration through different mechanisms. One such mechanism is proposed by Amior and Manning (2020), henceforth referred to as the *elasticities channel*. Under the assumptions that migrants have a less elastic labor supply than natives and that firms cannot wage discriminate between migrant and native workers, firms set a single wage that reflects the average labor supply elasticity of their workforce. Because migrants typically have lower reservation wages due to their more vulnerable conditions, their labor supply is less elastic, which allows firms to impose higher wage markdowns. As a result, in the absence of wage discrimination, migrant inflows can increase firms' average wage markdowns and, therefore, their labor market power.

This mechanism, however, relies critically on the assumption that firms cannot discriminate in wages between migrants and natives. While this assumption may be plausible in developed economies, where labor informality is relatively low, it is likely to be violated in developing countries such as Colombia, where informality in the manufacturing sector is approximately 60% (see, for instance, Arellano-Bover and San, 2020; Amodio et al., 2025; Dostie et al., 2023, for evidence on wage discrimination in developing countries). In this context, the vulnerable conditions under which many workers are employed imply a greater capacity for firms to discriminate between migrants and natives and to impose differential wage markdowns. This weakens the relevance of the average markdown effect emphasized by Amior and Manning (2020).

This paper proposes an alternative channel through which firms' labor market power in a developing country can be affected: the *self-employment channel*. As shown by Amodio et al. (2025), self-employment in developing countries operates as an outside option for wage workers, namely

those employed in a dependent relationship with a firm. The presence of a sizable self-employment sector therefore provides workers with an alternative if utility in wage employment is sufficiently low. As a result, the larger the self-employment sector in the local labor market faced by a firm, the stronger the outside option of wage workers and the lower the labor market power firms can exert. Intuitively, when self-employment represents a credible outside option, firms must limit wage markdowns to reduce the risk of losing workers.

In this context, if migration disproportionately affects self-employment income through increased competition between natives and migrants, it reduces the value of self-employment as an outside option for wage workers in the manufacturing sector and increases firms' labor market power. In the case of the Venezuelan exodus to Colombia, I provide evidence that this mechanism is at play. Accordingly, one would expect an increase in firms' labor market power driven by the *self-employment channel*.

4.2 Product Market Power: Markups

An often overlooked aspect of the economics of migration literature concerns its demand-side effects and how migrant inflows into host economies can alter the composition of consumers and, in turn, firms' market decisions. Only a limited number of papers analyze how migration affects the output side of product markets in host economies, and most of this work focuses on the housing market (Saiz, 2003, 2007; Kerr and Kerr, 2011; Gonzalez and Ortega, 2013; Olney, 2015; Howard, 2020; Cengiz and Tekgüç, 2022; Peri et al., 2022; Galaasen et al., 2025). Importantly, these studies typically rely on competitive product market frameworks and therefore abstract from the role of firm market power.

In this paper, I instead analyze how migration affects firms' output markets by focusing on changes in product market power arising from shifts in demand structure, specifically changes in the composition of consumers following a migration shock. According to Sangani (2022), in a model where household search intensity depends on the opportunity cost of time, the markup firms can impose in the output market depends directly on the income level of consumers. Building on this insight, this paper makes two related contributions.

First, I hypothesize that migration-induced changes in the income distribution of demand affect firms' ability to charge prices above marginal cost. In particular, during refugee crises or forced migration episodes, where migrants typically arrive under vulnerable economic conditions, the income distribution shifts toward lower-income consumers. This shift increases price sensitivity and reduces firms' output market power, leading to lower markups. This mechanism, however, is not exclusive to forced migration episodes. In the case of high-skilled or high-income migration, the income distribution of demand may shift in the opposite direction, potentially increasing firms' market power.

Second, given the wage-setting equation derived above, changes in product market power constitute an additional channel through which migration can indirectly affect wages. As shown earlier, a reduction in firms' output market power implies lower markups, which, all else equal,

put upward pressure on wages. Consequently, even in the absence of direct labor market effects, migration can influence wages through its impact on firms' pricing power.

4.3 Marginal Productivity of Labor

A migration shock can affect the marginal productivity of local labor through several channels. In the setting studied in this paper, under the assumption that native and migrant workers are perfect substitutes, an increase in the supply of Venezuelan workers would be expected to reduce the marginal productivity of local labor (Ottaviano and Peri, 2012; Peri, 2016). However, if migrants and natives are not perfect substitutes but instead are complementary within firms, migration can generate increasing returns to scale and raise the marginal productivity of the overall labor force. Such complementarities may arise if Venezuelan workers entering the manufacturing sector possess skills that complement those of Colombian workers, facilitating knowledge diffusion and task reallocation within firms, and thereby generating productivity gains (Beerli et al., 2021; Bahar et al., 2022; Lombardo and Peñaloza-Pacheco, 2025).

Overall, Venezuelan migrants in Colombia are, on average, at least as qualified as Colombian workers (Lebow, 2024). In the manufacturing sector, however, Venezuelan migrants appear to have self-selected into employment in a way that constituted a particularly high-skilled labor supply shock. This pattern is consistent with the fact that manufacturing is one of the sectors in Colombia characterized by relatively lower levels of informality, implying higher entry barriers for workers.

Consistent with this interpretation, Lombardo and Peñaloza-Pacheco (2025) show that this high-skilled labor supply shock improved firms' performance, influenced technology adoption decisions, and enhanced the quality of goods offered to the market, ultimately boosting export performance. Taken together, these findings suggest that the hiring of high-skilled Venezuelan workers increased labor productivity in Colombian manufacturing firms and strengthened complementarities between migrant and native workers.

5 Empirical strategy

In this section, I will briefly describe the methodology implemented to calculate the wage markdowns, product markups, and the labor marginal productivity of Colombian manufacturing firms by using the EAM. Then, I will explain the empirical strategy considered to obtain the reduced-form evidence on the impact of the Venezuelan exodus on firm outcomes.

5.1 Markdown and markup estimation

To estimate firm-level markdowns, I follow the procedure suggested by Yeh et al. (2022). According to the authors, under the assumptions that (i) firms engage in cost minimization; there exists a flexible input k' such that (ii) there are no adjustment costs for that input; (iii) it is not subject to market power; (iv) it is chosen statically, and (v) it is used only for production, then firm i's markdown can be estimated; and finally if the production function of firm i $F(.)$ is twice continuously

differentiable and satisfies Inada conditions facing a continuously differentiable product demand schedule that is strictly decreasing, then the markdown (ν_{it}) of firm i in period t is going to be given by:

$$\nu_{it} = \frac{\theta_{it}^{l}}{\alpha_{it}^{l}\mu_{it}}$$

Where θ_{it}^{l} is the output elasticity of labor and α_{it}^{l} is the share of labor in the revenues of firm i in period t, and, finally μ_{it} is the markup that firm imposes in the product market. To estimate the product market markup of the firm μ_{it}, one needs to use the flexible input output-elasticity and share on revenues. According to De Loecker and Warzynski (2012) then, the markup is given by:

$$\mu_{it} = \frac{\theta_{it}^{k'}}{\alpha_{it}^{k'}}$$

Where $\theta_{it}^{k'}$ and $\alpha_{it}^{k'}$ are the output-elasticity and the share on revenues, respectively, of flexible input k' of firm i in period t. Although the labor and flexible input shares in the revenues of the firms can be calculated directly from the data, in order to obtain the output elasticity of both factors of production, I need to estimate the production function of the firms. To do so, I follow the economic literature and estimate the production function by implementing a proxy variable procedure (See, for instance, De Loecker and Warzynski, 2012; Ackerberg et al., 2015; Gandhi et al., 2020). In my main specification, I consider a general second-order trans-log production function specific to each 2-digit industry, such that the output elasticities of the production factors vary across firms and over time. However, in Section 9, I conduct several robustness exercises to demonstrate that my results remain unchanged when different production functions are assumed.

For the case of the markups estimations, Bond et al. (2021) raises some concerns about how by using revenue data the markup imposed by firms should be trivially equal to one and, therefore, all estimates by using a flexible-input approach could be purely statistical noise. In the case of this paper, one of the advantages of the EAM database from Colombia, is that it contains information on price and quantity of outputs. Given this, I follow Fieler et al. (2018) and build firm-specific price indices to calculate firms' output in terms of quantity, therefore providing more confidence in the markup estimations (see Appendix D for further details). Descriptive statistics related to the estimated market power of firms in both the labor and product market are provided in Appendix C.

5.2 Reduced form evidence

To study the impact of the Venezuelan migration on firm outcomes, I estimate the following first-difference specification:

$$\Delta y_{imjt} = \omega_j + \beta_t \Delta M_{m,2018} + X_m^{'}\delta + \Delta\varepsilon_{imjt} \tag{6}$$

Where Δy_{imjt} is the outcome variable change of firm i in local labor market m, industry j between period t and the baseline year (2015) before the beginning of the exodus. In this paper, the

main outcomes under study are the total number of employees, output (measured in quantities), marginal productivity of labor, average wage, wage markdown, and price markup—all expressed in logarithmic form. Additionally, I will analyze the impact on firms' profits (in logs) and on entry.

$\Delta M_{m,2018}$ is the change in the stock of Venezuelans living in local labor market m between 2015 and 2018 relative to the population of that local labor market; ω_j are 4-digit industry fixed effects which control for shocks that occurred between year t and the baseline period that affected differentially firms in different economic activities; $X_m^{'}$ are pre-exodus local labor market characteristics, such as local labor market fiscal revenues and expenditures in the past, per capita GDP, multidimensional non-monetary poverty rate, Gini coefficient, the share of individuals with subsidized health coverage, coca crop hectares cultivated, homicide rate, national transfers from the central Government, the number of terrorist attacks, and the total amount of exports to Venezuela for each local labor market in the past, which control for any shocks that affected different local labor markets in my sample, and that are explained by these characteristics. Finally, ε_{imjt} is the standard error of the specification which is clustered at the local labor market level.

The coefficient of interest is β_t which captures the impact on the outcome variable of interest of a change in the share of migrants that moved to each local labor market after 2015. I run a separate regression for each year and store the coefficients β_t to show them in an event-study type figure.

Instrumental Variable. Given that the share of migrants in each local labor market is not random, I follow the economic literature and use an instrumental variable approach to estimate consistent causal coefficients (Ibáñez et al., 2021; Caruso et al., 2021; Peñaloza-Pacheco, 2022; Lombardo and Peñaloza-Pacheco, 2025; Lombardo et al., 2025). I take advantage of the forced nature of the Venezuelan exodus in Colombia and the fact that due to proximity and lack of resources, migrants were disproportionately located in the local labor markets closer to the border between Colombia and Venezuela, and use the inverse distance between Colombia and Venezuela as an instrumental variable. More specifically, my first-stage regression is the following:

$$\Delta M_{m,2018} = \alpha + \theta_1 D_m^{-1} + X_m^{'}\delta + \epsilon_m \tag{7}$$

Where D_m denotes the minimum distance between each local labor market m in the sample and the Venezuelan states situated in the two main border crossing points between the countries: Puente Simón Bolivar in Norte de Santander and Paraguachón in La Guajira. Finally, X_m is the same vector of local labor market controls presented above. The main identifying assumption of the empirical approach is that, once I control for the pre-determined vector of local labor market characteristics and industry fixed effects, then there are not other changes at the local labor market level explained by the distance variable that affect firms' outcomes during the analysis period. As can be seen in Table A.1 of the Appendix, the first-stage regression is statistically significant indicating that the distance is a good exogenous predictor of the share of migrants located in each local labor market during the time in which the exodus took place.

6 Main Results

In this section, I provide the empirical results of the main estimates evaluating the effect of the Venezuelan exodus on firm outcomes. The results are shown in Figure 3, presented in an event-study format.

Employment. First, I analyze the impact of the Venezuelan exodus on employment within firms in the Colombian manufacturing sector. Panel (a) of Figure 3 indicates that prior the reopening of the borders, there were no differential trends in terms of employment (in logs) that could be attributed to the share of Venezuelan migrants. However, starting in 2016, a significant upward trend emerges, leading to an increase in the total number of employees hired by the firms over time. My estimates suggest that by 2020, employment increased by approximately 6% relative to the baseline period in response to a 1 percentage point (p.p.) increase in the share of migrants in the local labor market.

Output. Next, I assess the impact of migration on the total output of firms, measured in quantities. Panel (b) of Figure 3 suggests that a 1 p.p. increase in the share of migrants at the local labor market level increased the total output of the firms by approximately 5%, with this effect remaining relatively stable over time. Two potential mechanisms could explain this outcome.

First, the observed increase in employment shown in Panel (a) of Figure 3 may have translated into higher output through a scale effect—namely, hiring more migrants enables firms to produce more. Second, considering general equilibrium effects of the migration shock, this result could also reflect demand-side response to migration; as the migrant population in the local market grows, firms may face higher demand for their products, which in turn could have driven increased production.

Marginal Productivity of Labor. Given the previous results on output and employment, the key variable of interest to look at is the marginal productivity of labor. The results, shown in Panel (c) of Figure 3, suggest that a 1 p.p. increase in the share of Venezuelan migrants led to an average increase of approximately 3% in the marginal productivity of labor in Colombian manufacturing firms relative to the baseline period. These findings imply that hiring Venezuelan workers enhanced labor productivity, likely due to the skills and abilities that migrants contributed to the economy.

These results are consistent with Lombardo and Peñaloza-Pacheco (2025), who demonstrate that Venezuelan migration exerted a firm-level upgrading effect on manufacturing firms in Colombia. Their analysis shows that, following the exodus, firms increased their hiring of high-skilled workers—particularly in R&D-related tasks—which translated into greater investment in R&D, improved production techniques, and enhanced organizational practices. Ultimately, these adjustments contributed to improvements in product quality and export performance. A similar effect is observed when using output per workers as a measure of labor productivity, as shown in Figure A.2 of Appendix A.

Wages. I examine the impact of the Venezuelan exodus on the average wages paid by firms in

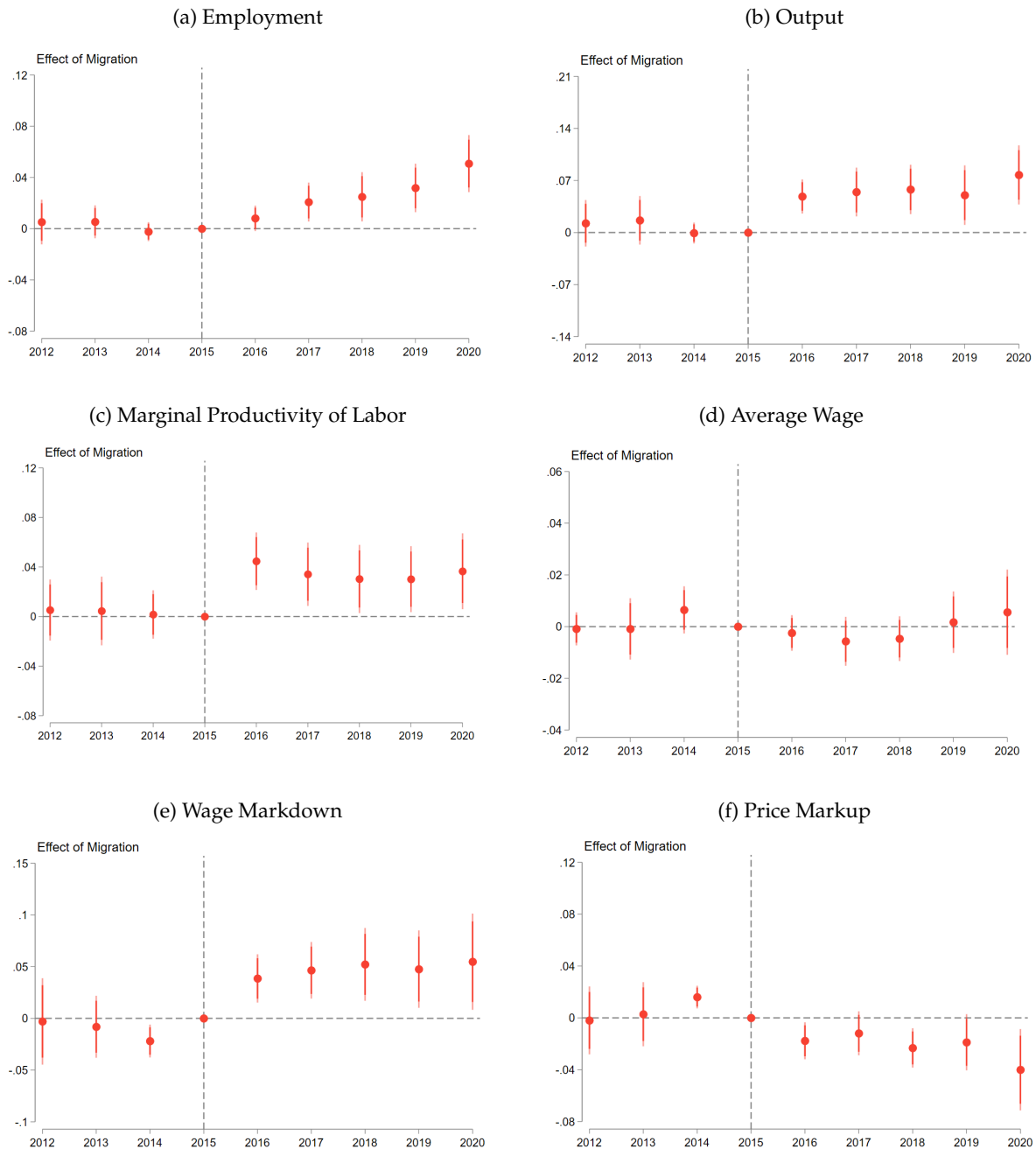
the manufacturing sector. The results are presented in Panel (d) of Figure 3. Despite the observed increase in the marginal productivity of labor depicted in Panel (c), wages remained relatively stable and did not exhibit a corresponding positive impact.

Under a competitive framework, these findings are somewhat puzzling, as wages should reflect marginal labor productivity. Consequently, the positive effect on productivity identified earlier should have translated into higher wages paid by firms. However, if we shift from a purely competitive framework to one in which firms possess market power in both labor and product markets, a gap may exist between the actual wages and the labor productivity—arising from wage markdowns and price markups. In such a setting, a change in either of these elements could help rationalize the absence of significant wage effects observed in the estimates. These results are illustrated in Panel (e) and (f) of Figure 3.

Finally, to rule out the possibility that the estimated effects mask offsetting heterogeneity, I re-estimate the effect on average wages by splitting the firm-level labor force into white- and blue-collar workers. Figure A.3 in Appendix A reports these results. The estimates are very similar across groups and confirm the null effect found in the aggregate estimates reported in Panel (c) of Figure 3.

Wage Markdowns. Panel (e) of Figure 3 presents the main estimates of the Venezuelan exodus impact on the labor market power of firms in the Colombian manufacturing sector. It reveals that firms more exposed to migration increased the wage markdowns imposed in the labor market following the exodus. Specifically, my estimates suggest that a 1 p.p. increase in the share of migrants relative to the local labor force increased wage markdowns by approximately 6%, on average. Moreover, this effect did not seem to dissipate over time but remained stable in the years following the reopening of the borders.

Figure 3: Impact of the Venezuelan exodus on Manufacturing Firms Outcomes, 2012-2020



Notes. Each figures shows the estimated coefficients of equation 6 separately for each year. The estimates include Industry fixed effects at the 4-digit CIIU level. They also control for the Local Labor Market (LLM) controls specified in Section 5.2. The bars represent the 95% (light bars) and 90% (darker bars) confidence intervals. Standard errors are clustered at the level of the local labor market level. Source: Own estimates based on EAM data from DANE.

To contextualize these figures in dollars terms, we know from Appendix C that Colombian manufacturing workers were receiving about 55 cents per dollar of marginal output due to firm labor market power. Based on my estimates and an average increase of approximately 2.5 p.p. in the migrant share at the country level, workers now receive roughly 48 cents per dollar produced,

implying an increase of about 7 cents in the rents firms extract from workers per dollar of output following the exodus.

Price Markup. Finally, Panel (f) of Figure 3 indicates that firms' product market power, as reflected in price markups, was also influenced by the Venezuelan exodus. My estimates suggest that a 1 p.p. increase in the share of migrants reduced by approximately 2.4% firm market power in the goods market.

As previously mentioned, migration not only alters the supply and composition of the labor force but also constitutes a demand shock to domestic markets, with significant implications for how firms interact with the newly arriving consumers. Venezuelan migrants, on average, had considerable lower income levels, which implies a higher demand price-elasticity (Sangani, 2022). This higher elasticity could have constrained firms' ability to extract rents from consumers, since the overall markup would now be a weighted average of the markup they impose on native consumers and the lower markup they can impose on migrant consumers.

The results presented so far highlight four key findings, summarized in equation 8. First, the migration shock generated by the Venezuelan exodus constituted a high-skilled labor supply shock in the manufacturing sector, increasing the marginal productivity of labor by approximately 3% following a 1 p.p. increase in the migrant share. This productivity gain enabled firms to expand employment and increase total output. Second, the larger supply of Venezuelan workers in local labor markets increased firms' wage markdowns by approximately 6%, allowing firms to capture productivity gains without translating them into higher wages. Third, the Venezuelan exodus was not only a labor supply shock but also a demand shock that altered the income composition of local demand. Because migrants entered Colombia with lower incomes, firms' ability to set prices above marginal cost declined, leading to a 2.4% reduction in price markups in the manufacturing goods market. Finally, considered jointly—and in the presence of a negligible effect on output prices of -0.25%[2]—these mechanisms account for the null effect on average wages paid by firms (-0.36%), despite the substantial increase in labor productivity in the manufacturing sector.

$$\underbrace{\log(w)}_{\substack{-0.36\% \\ (0.44)}} = \underbrace{\log(\text{MPL})}_{\substack{3.26\% \\ (0.69)}} - \underbrace{\log(\text{Mark-down})}_{\substack{5.74\% \\ (0.97)}} - \underbrace{\log(\text{Mark-up})}_{\substack{-2.37\% \\ (0.89)}} + \underbrace{\log(\text{p})}_{\substack{-0.25\% \\ (0.39)}} \tag{8}$$

7 Mechanisms

7.1 Marginal Productivity of Labor

The main results document a 3% increase in the marginal productivity of labor following a 1 p.p. increase in the migrant share. This section provides evidence on the mechanisms driving this result. In a general equilibrium setting, a migration shock can raise MPL through three non-exclusive

[2] Results available upon request.

channels: a demand-driven scale expansion, an input complementarity channel operating through intermediate inputs and capacity utilization, and skill complementarities between migrant and native workers. I provide evidence consistent with each of these channels.

Demand channel. Migration constitutes not only a labor supply shock but also a demand shock, as newly arrived migrants increase local expenditure on goods produced by Colombian manufacturing firms. If demand expands more rapidly than hiring, firms scale up output relative to employment and MPL rises. To assess whether this mechanism is operative, I exploit variation in firms' reliance on local demand, using transportation costs as a proxy for the geographic reach of firms' customer base. Firms with below-average transportation cost shares relative to peers in the same department and four-digit industry are more likely to serve local consumers and are therefore more directly exposed to the demand generated by migrant inflows. The results, reported in Table A.4, shows that the increase in output, labor, and MPL reported in Figure 3 is concentrated among firms relying on local demand. This pattern points to a demand-driven scale expansion as a central force behind the productivity gains.

Input scaling and capacity utilization channel. A demand-driven expansion can raise MPL even absent a technology shift if firms respond by scaling up variable inputs while capital remains fixed. Figure A.4 presents event-study estimates of the migration shock's effect on each input in the production function: intermediate materials, capital, and energy. Three patterns emerge. First, materials use increases significantly in the two to three years following the onset of the exodus, consistent with firms expanding their use of variable inputs alongside labor. Second, energy consumption rises in parallel with output, employment, and materials. Since energy consumption in manufacturing closely tracks the operational intensity of installed machinery, this increase serves as evidence that firms were running their capital stock more intensively following the shock. Third, the capital stock shows no significant response, remaining stable throughout the analysis period. Taken together, these patterns suggest that the demand shock was accommodated primarily through variable inputs rather than through new investment, consistent with firms having operated below full capacity prior to the exodus.

To formalize this interpretation, Figure A.4 reports event-study estimates of the energy-to-capital ratio (E/K), which serves as a proxy for capacity utilization in the absence of direct utilization data. Following the onset of the exodus, E/K rises significantly, indicating that each unit of installed capital was operated more intensively after the shock—consistent with idle capacity being activated rather than new capital being installed.

As a direct test of this mechanism, Panel B of Table A.4 reports heterogeneous treatment effects on output, MPL, and labor by firms' pre-shock capacity utilization, proxied by the capital-to-energy ratio in the pre-exodus period. Firms with a high pre-shock capital-to-energy ratio were using their installed capital at a relatively low intensity and therefore had more slack to accommodate a demand expansion. The results show that the largest increases in output and MPL are precisely concentrated among these high-slack firms, while firms that were already operating near capacity exhibit smaller responses. This pattern is not easily explained by the labor supply or skill composition channels alone, and instead points directly to capacity utilization as a key margin of adjustment.

Skill complementarity channel. Finally, MPL may have risen in part due to the relatively high skill content of Venezuelan workers who entered manufacturing employment. As documented in Table 1, Venezuelans employed in manufacturing are more likely to hold post-secondary education than their Colombian counterparts, a differential that exceeds the gap observed in the overall workforce. If Venezuelan workers are more productive than the average Colombian worker in manufacturing — as captured by the parameter ϑ in the model's labor composite — then firms hiring more Venezuelans will exhibit higher average firm-level MPL, even absent any change in the productivity of native workers. To test this, I estimate whether the MPL response is larger in industry–local labor market cells with greater exposure to Venezuelan workers, using GEIH data to compute the share of Venezuelans in each cell and imputing this exposure to all firms within it. The results, reported in the last two columns of A.2, indicate that the estimated effect on MPL is nearly three times larger for firms in high-exposure cells than for the full sample. This is consistent with the productivity differential between Venezuelan and Colombian workers raising the average MPL of firms that hired more migrants, and aligns with the firm-level upgrading findings of Lombardo and Peñaloza-Pacheco (2025).

Taken together, these three mechanisms—demand-driven scale expansion, capacity utilization, and skill complementarities—jointly account for the increase in MPL documented in Figure 3.

7.2 Wage markdowns

In this section, I provide evidence to disentangle the potential mechanisms underlying the main results presented above. I first present evidence consistent with the hypothesis that the increase in wage markdowns is driven by a reduction in the value of self-employment as an outside option for manufacturing wage workers.

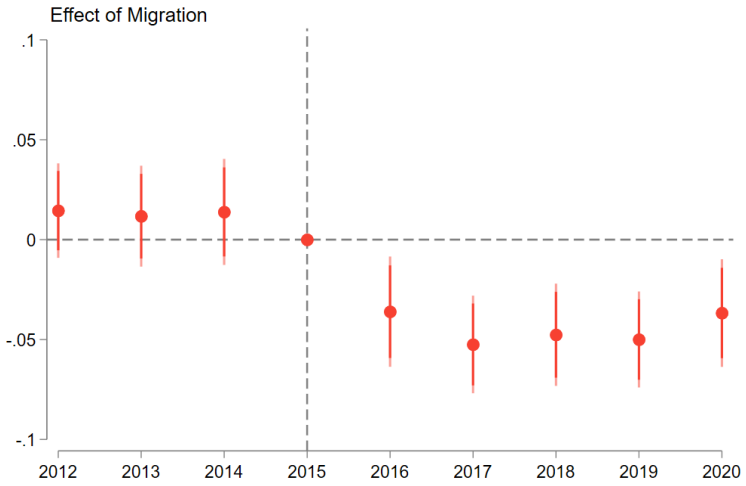
I present two pieces of evidence. First, Figure 4 reports estimates from the baseline specification in equation 6, re-estimated at the local labor market level with the average labor income of native self-employed workers (in logs) as the outcome variable. Prior to the Venezuelan exodus, there is no evidence of differential pre-trends associated with changes in the migrant share across local labor markets. Beginning in 2016, however, I document a significant decline in average self-employment income. The estimates indicate that, in subsequent periods, self-employment income fell by approximately 5% relative to the baseline period in response to a 1 p.p. increase in the migrant share of the local labor market.

This pattern is consistent with the way Venezuelan migrants initially integrated into the Colombian labor market. Because most migrants arrived without proper documentation or work permits, their employment opportunities were largely restricted to self-employment or informal wage work. As a result, migrants became disproportionately concentrated in the self-employment sector, increasing competition and reducing the value of self-employment.

As discussed in Section 4, Amodio et al. (2025) show that self-employment in developing countries serves as an outside option for wage workers that disciplines firms' labor market power. By lowering the value of this outside option, the migration shock increased firms' ability to pay wages below

workers' marginal productivity, allowing firms to capture a larger share of the productivity gains generated by the Venezuelan exodus.

Figure 4: Impact of the Venezuelan exodus on Self-employment Income, 2012-2020



Notes: The figure reports estimates from equation 6 at the local labor market level. The outcome variable is the average labor income of informal self-employed workers (in logs) in each local labor market. Source: Authors' calculations based on GEIH data from DANE.

This mechanism is particularly relevant in settings characterized by large migration episodes, especially in developing countries. It implies that increases in firms' labor market power—and the associated adverse effects on native wage workers—can arise even in the absence of direct competition between migrants and natives within firms. In other words, because migration affects labor market power through workers' outside options rather than through direct substitution, wages may decline even when migrants and natives do not compete for the same jobs. In this case, wage effects are driven not by labor supply competition, but by an expansion of firms' wage-setting power.

Additional evidence consistent with this mechanism is provided in the second and third columns of Table A.2, which estimate heterogeneous effects of the migration shock on wage markdowns across firms. Specifically, I compare the baseline estimates (second column) with those obtained by restricting the sample to firms operating in industry-local-labor-market cells in which, according to the Colombian Household Surveys, no Venezuelan migrants were employed during the post-exodus period (third column). The estimated increase in wage markdowns for this subgroup is very similar to the overall estimates. This finding indicates that the rise in firms' labor market power was not mainly driven by changes in workforce composition at the firm level, but is instead consistent with a decline in the value of self-employment as an outside option induced by the migration shock.

Finally, to shed light on the sources of the productivity gains documented above, I re-estimate the main marginal product of labor (MPL) results focusing on firms operating in industry–local-labor-market cells with high migrant exposure in manufacturing during the post-exodus period. To construct this measure, I use household survey data to compute, for each four-digit industry and local labor market, the share of Venezuelan workers in the total labor force over the post-exodus period, and I impute this share to all firms in the corresponding industry-local labor market cell. I

classify firms as high-exposure firms if their imputed migrant share lies in the top five percent of the exposure distribution.

The results are presented in the last two columns of Table A.2, which report the overall effect on MPL (in logs) and the corresponding estimate for firms in high-exposure cells. The estimates indicate that, in cells with high migrant employment, the effect on MPL is nearly three times larger than the average effect across all firms. This evidence suggests that productivity gains in the manufacturing sector were driven primarily by the skills and knowledge brought by Venezuelan migrants, with firms that hired more migrants experiencing larger increases in their MPL.

7.3 Product markups

I next provide evidence consistent with a local demand composition channel affecting firms' price markups. If the decline in markups documented in the main results is driven by an inflow of relatively low-income, more price-sensitive consumers following the migration shock, then firms that rely more heavily on local demand should experience larger reductions in product market power than firms that sell to international or distant domestic markets.

Table A.4 presents two exercises that support this interpretation. First, in the second and third columns, I exploit information from the EAM on whether firms sell to international markets and split the sample into exporters and non-exporters. Exporters are defined as firms whose export share of total sales lies in the top third of the distribution. Because exporters are more exposed to international competition, they are expected to face lower price-setting power and to be less affected by changes in local demand composition. Consistent with this intuition, the estimates indicate that the negative effect of migration on markups is concentrated entirely among non-exporters, with no significant effect for exporting firms.

Second, even among non-exporters, firms may differ in the extent to which they rely on very local demand versus sales to other domestic markets. While I cannot directly observe the geographic location of firms' customers, I proxy for demand proximity using firms' expenditures on transportation costs related to the sale and delivery of their products. Firms that incur relatively low transportation costs are more likely to serve local consumers, whereas firms with higher costs are more likely to sell to more distant markets within the country (Oberfield et al., 2024).

I construct a measure of local market reliance by comparing each firm's transportation cost share of output to the average share among firms in the same department and 4-digit industry.[3] I then re-estimate the markup regressions separately for firms more and less reliant on local demand. The results, reported in the last two columns of Table A.4, show that the decline in markups is concentrated among firms with relatively low transportation costs, that is, firms that are more dependent on very local demand.

Taken together, these results provide suggestive evidence that the migration shock altered the

[3] This comparison within department–industry cells ensures that firms selling similar products are compared and accounts for differences in transportation costs related to the geographic size of departments.

composition of local demand in a way that increased the price elasticity faced by firms operating primarily in local markets. As a consequence, firms more exposed to local consumers—particularly those with lower exposure to international or distant domestic markets—experienced the largest reductions in price-setting power.

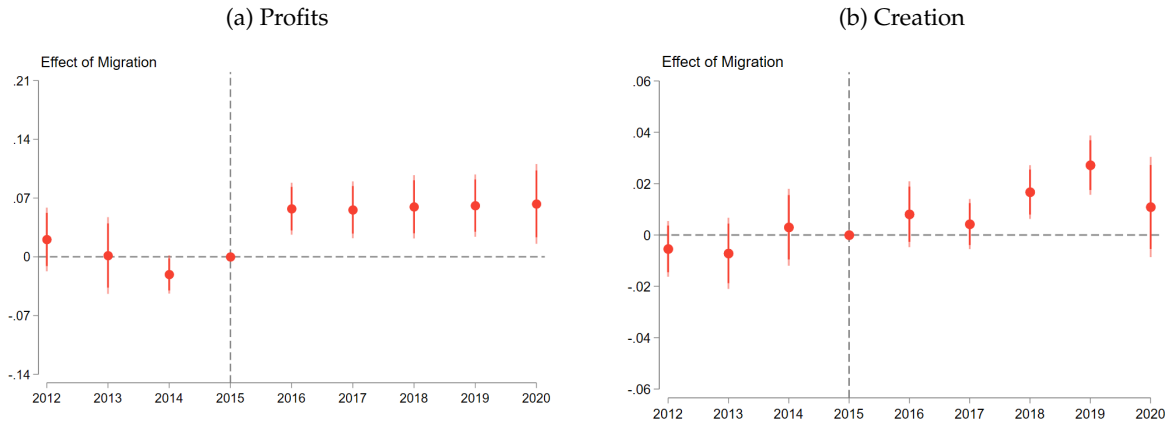
8 Medium-run impacts: Firms' profits and dynamics

The results presented so far indicate that, although labor productivity increased as a consequence of the migration shock in Colombia, this did not translate into higher wages for workers. This suggests that firms may be capturing a larger share of the benefits generated by increased productivity. However, it is also crucial to consider the effects of markdown and markup margins. An increase in wage markdowns could enhance firm profits, but a reduction in markups would imply a decrease in profits, as it reflects a lower ability to charge prices above marginal costs to consumers. Therefore, understanding how profits evolve following a migration shock within a non-competitive framework is primarily an empirical question.

I estimate the impact of migration on firm profits. The results are shown on the left-hand side of Figure 5. Before the exodus, there were no differential trends explained by the share of migration relative to the baseline period. However, after the exodus started, profits not only increased but continued to do so over subsequent years. My estimates, controlling for pre-determined local labor market characteristics, suggest that firm profits increased by approximately 6% relative to the pre-exodus baseline.

These higher profits could be explained by the increase in the marginal productivity of labor, as well as by the higher wage markdowns that firms could impose due to the labor supply shock. Although a reduction in product price markups could potentially limit the ability of firms to secure higher profits, the decline was not significantly large to offset the benefits derived from increased productivity and wage markdowns.

Figure 5: Impact of the Venezuelan exodus on Medium-run Outcomes, 2012-2020



Notes. Each figures shows the estimated coefficients of equation 6 separately for each year. The estimates include Industry fixed effects at the 4-digit CIIU level. They also control for the Local Labor Market (LLM) controls specified in Section 5.2. The bars represent the 95% (light bars) and 90% (darker bars) confidence intervals. Standard errors are clustered at the level of the local labor market level. Source: Own estimates based on EAM data from DANE.

Finally, under conditions of free entry, higher profits are expected to incentivize the creation of new firms to capitalize on the increased profitability of the manufacturing sector resulting from the Venezuelan labor supply shock. My estimates of firm creation, shown on the right-hand side of Figure 5, confirm this expectation. They indicate that, following the migration shock, firm creation increased by approximately 2 p.p. in 2019 in response to a 1 p.p. increase in the migrant share.

9 Robustness Checks

In this section, I present different robustness exercises related to the main empirical results in the paper.

Alternative Production Functions. In the main results presented in the paper, a 2-digit industry specific second-order translog production function was assumed. As was mentioned above, this approach has several advantages as it does not impose that the production function has to be the same across firms in different industries within the manufacturing sector nor that the output-elasticities of the production inputs has to be constant over time nor the same across firms within the same sector. As robustness exercises, I estimate different alternatives by considering a Cobb-Douglas production function rather than a second-order translog, and by imposing that the second-order translog production function is the same across industries in the manufacturing sector, namely, by estimating the production functions for all firms at once and not sector by sector. The results of these exercises along with a discussion of the implications for each approach are presented in section B.1 of Appendix B.

Identification under the proxy variable method. According to Gandhi et al. (2020), when using the proxy variable approach to estimate gross output production functions, additional sources of variation in demand for flexible inputs are necessary. They suggest that time-series variation in

aggregate price indexes for flexible inputs can serve as such a source, especially when analyzing long-panel datasets—the 10-year data span of this paper sufficiently meets this criterion.

Alternatively, Flynn et al. (2019) propose imposing a specific returns-to-scale assumption, namely constant returns to scale (CRS), which enables point identification of the production function (other papers considering this method are, for instance, Yeh et al., 2022; Estefan et al., 2024). Following this approach, I re-estimated the second-order translog production functions under the CRS assumption. The results, presented in section B.2 of Appendix B, indicate that the estimates of markups, markdowns, and marginal productivity of labor—along with the effect of migration on the main outcomes—remain very similar to the original estimates.

Multi-product and quality considerations. As a robustness check, I re-estimate the effect of migration on markups by restricting the sample to single-product firms and to firms producing homogeneous goods, for which product quality and variety play a limited role. This restriction addresses concerns in the recent literature that markup estimates in differentiated-product industries may be distorted by unobserved changes in product quality or in the range of products produced by the firm (De Roux et al., 2021). Even with physical quantity data, such changes can contaminate production-based markup measures, making it difficult to isolate genuine shifts in market power. Focusing on firms producing a single, standardized product therefore reduces the scope for quality or assortment-driven bias in the estimated markup effects.

Single-product firms are defined as firms producing only one 7-digit CPC product in the pre-exodus period, based on the DANE classification. Homogeneous-good firms are those for which at least 75% of total output in the pre-exodus period corresponds to a homogeneous product, defined at the 3-digit CPC level as energy products, raw minerals, construction inputs, and basic ferrous and non-ferrous metals. These products are characterized by standardized properties and negligible scope for within-product quality differentiation.[4]

Results are reported in Table B.1 and are consistent with the main estimates. If anything, the estimated effect of migration on markups is larger for homogeneous-good producers, consistent with these firms operating in highly substitutable markets where changes in local demand elasticities have a stronger impact on markup decisions.

Leave-one-out estimates. Next, I rule out the possibility that my estimates are primarily driven by the most important local labor markets or 2-digit industries in my sample. To do this, I present the main results from Section 6 using a leave-one-out approach, systematically omitting the local labor markets and 2-digit industries with the largest number of firms. Specifically, for local labor markets, I exclude Bogotá, Medellín, Cali, Barranquilla, and Santander. For the 2-digit industries, I exclude Chemicals, Iron, Rubber/Plastic, Textiles, and Food. The results of these robustness checks are shown in sections B.3 and B.4 in Appendix B.

Alternative independent variable definition. Finally, I change the independent variable definition by considering not the share of Venezuelan migrants relative to the local population, but instead the share relative to the local labor force and the employed population in each local labor market. The results of this exercise are presented in section B.5 of Appendix B.

[4] See the footnote to Table B.1 for details.

10 Model

To rationalize the empirical findings, this section develops a tractable general equilibrium model to analyze the implications of a migration shock in a non-competitive framework, incorporating the key mechanisms highlighted in the empirical analysis. The model allows both wage markdowns and price markups to adjust endogenously in response to the migration shock.

Following Amodio et al. (2025), the wage markdowns that firms can impose on their workers depend on the attractiveness of self-employment—an outside option individuals consider in their occupational choice—as well as on the composition of migrants and natives within firms. In line with Ulyssea (2018), once individuals self-select into wage employment or self-employment, firms face a trade-off between hiring workers formally or informally, governed by convex costs of informal hiring that are heterogeneous across natives and migrants. Finally, on the product market side, markups are determined by demand elasticities of substitution across varieties and sectors, which differ between natives and migrants.

10.1 Setup

Environment: There is a continuum of local labor markets $k \in [0, 1]$. Labor markets are segmented across k and workers cannot move across markets, but goods are traded so households consume goods from all markets. Within each local labor market k there are two sectors: self-employment S and firm sector F. In sector F, a mass M_k of firms operate endogenously, determined by the entry cutoff z_k^*.

Labor Supply: There are two types of workers, indexed by j: natives (n) and migrants (m), with $j \in \{n, m\}$. Workers are heterogeneous and possess sector-specific abilities, represented by their endowment of efficiency units of labor $a_j = (a_{jF}, a_{jS}) \sim G(a_{jF}, a_{jS})$, where $G(\cdot)$ is a joint Type I extreme value (GEV) distribution with shape parameter θ_j. It is assumed that $\theta_n > \theta_m$, implying that migrants exhibit a lower elasticity of occupational choice between firm employment and self-employment than natives.

Let w_{jFk} and w_{Sk} denote the wage per efficiency unit earned by workers of type j in market k in the firm and self-employment sectors, respectively. Workers take sectoral incomes per efficiency unit as given and self-select into either self-employment or the firm sector in order to maximize utility. Specifically, each worker chooses the sector that solves max $\{u_{jF}, u_{jS}\}$, where utilities in firm employment and self-employment are given by:

$$u_{jF} = \ln(w_{jFk}) + a_{jF} \qquad u_{jS} = \ln(w_{Sk}) + a_{jS} \tag{9}$$

The joint distribution CDF of (a_{jF}, a_{jS}) is given by:

$$G\left(a_{jF}, a_{jS}\right) = \exp\left[-(e^{-\theta_j a_{jF}} + e^{-\theta_j a_{jS}})\right] \tag{10}$$

Then the supply of workers j in each sector is going to be given by:

$$L^s_{jFk} = \Xi_{jFk} N_{jk} = \frac{(w_{jFk})^{\theta_j}}{(w_{jFk})^{\theta_j} + (w_{Sk})^{\theta_j}} N_{jk} \qquad L^s_{jSk} = \Xi_{jSk} N_{jk} = \frac{(w_{Sk})^{\theta_j}}{(w_{jFk})^{\theta_j} + (w_{Sk})^{\theta_j}} N_{jk} \tag{11}$$

Where Ξ_{jFk} and Ξ_{jSk} are the probabilities of individuals of type j working in the firm and self-employment sectors in market k, respectively, and N_{jk} is the number of workers j in market k, which is given.

Demand: There are two types of households—natives and migrants—indexed by $j \in \{n, m\}$, where each type consists of a continuum of identical households. Let N_{jk} denote the mass of type-j households (equivalently, workers) in market k. Each household is endowed with one unit of time, which can be allocated between firm employment (F) and self-employment (S). The representative household of type j in local labor market k' has Cobb–Douglas preferences over the consumption of market-level output $\{C_{jk}\}_{k\in[0,1]}$, given by:

$$C_{jk'} = \exp\left\{ \int_0^1 \alpha_{jk} \log C_{jk}(k') dk \right\} \tag{12}$$

with expenditure shares equal to $\{\alpha_{jk}\}_{k\in(0,1)}$ with $\int_0^1 \alpha_{jk} dk = 1$. Here, $C_{jk}(k')$ denotes consumption by a type-j household residing in k' of the composite good produced in origin market k. Each good C_k comes in two varieties: $\{C_{Fk}, C_{Sk}\}$ which are produced by firms F or self-employees S. Each firm i in sector F produces a differentiated variety of the goods C_{Fk} denoted by c_{iFk}. The consumption of consumers j is given by:

$$C_{jk} = \left[\beta_j C_{jFk}^{\frac{\rho_j - 1}{\rho_j}} + C_{jSk}^{\frac{\rho_j - 1}{\rho_j}} \right]^{\frac{\rho_j}{\rho_j - 1}} \qquad C_{jFk} = \left(\sum_{i=1}^{M_k} c_{ijFk}^{\frac{\eta_j - 1}{\eta_j}} \right)^{\frac{\eta_j}{\eta_j - 1}} \qquad \rho_j, \eta_j > 1, \eta_j > \rho_j \tag{13}$$

Where $\eta_m > \eta_n > \rho_m > \rho_n$. Namely, migrants are more sensitive to price changes than natives within and across sectors in a specific market.

The income $I_{j,k}$ of household j is given by $I_{jk'} = w_{jFk'} L_{jFk'} + w_{Sk'} L_{jSk'} + \Pi_{jk'}$ where $L_{jFk'} + L_{jSk'} = N_{jk'}$. $w_{jFk'}$ is the firm-sector wage for type j, $w_{Sk'}$ is the self-employment earnings per efficiency unit, and $\Pi_{jk'}$ is profit of the firm-sector. From this problem:

$$P_{jFk} C_{jFk} = \gamma_{jFk} \alpha_{jk} I_{jk'} \qquad P_{Sk} C_{jSk} = \alpha_{jk}(1 - \gamma_{jFk}) I_{jk'} \qquad r_{ijFk} = p_{iFk} c_{ijFk} = s_{ijFk} \gamma_{jFk} \alpha_{jk} I_{jk'} \tag{14}$$

where $s_{ijFk} = \left(\frac{p_{iFk}}{P_{jFk}}\right)^{1-\eta_j}$ denotes the share of demand for firm-sector goods accounted for by firm i, relative to total firm-sector demand. The terms $\gamma_{jFk} = \beta_j^{\rho_j} \left(\frac{P_{jFk}}{P_{jk}}\right)^{1-\rho_j}$ and $\gamma_{jSk} = \left(\frac{P_{Sk}}{P_{jk}}\right)^{1-\rho_j}$ represent the shares of expenditure allocated to firm-produced and self-employment-produced goods, respectively, with $\gamma_{jFk} + \gamma_{jSk} = 1$. Finally, $P_{jFk} = \left(\sum_{i\in M_k} p_{iFk}^{1-\eta_j}\right)^{\frac{1}{1-\eta_j}}$ and $P_{jk} = \left(\beta_j^{\rho_j} P_{jFk}^{1-\rho_j} + P_{Sk}^{1-\rho_j}\right)^{\frac{1}{1-\rho_j}}$ are the corresponding price indices.

Technology - Self-employment: Goods in sector S are produced with a linear technology, $Q_{Sk} = L_{Sk}$ such that $L_{Sk} = \sum_{j\in\{n,m\}} L_{jSk}$. Self-employment is perfectly competitive, so zero profits imply $P_{Sk} = w_{Sk}$. Market clearing requires $Q_{Sk} = \sum_{k'} \sum_{j\in\{n,m\}} C_{jSk}(k')$. Self-employment income for type j in market k equals $w_{Sk} L_{jSk}$ and enters household income.

Technology - Firm sector: Each firm in the firm sector operates a unit of installed capital ($K = 1$, normalized) and chooses how intensively to utilize it. Given a firm-specific exogenous productivity term z_{iFk} and capacity utilization $u_{iFk} \in (0, 1]$, the production function is

$$q_{iFk} = z_{iFk}\, u_{iFk}^{\beta_K}\, \Psi_{iFk}^{1-\beta_K} \tag{15}$$

where $\beta_K \in [0, 1)$ governs capital intensity and the CES labor–materials composite is defined as

$$\Psi_{iFk} \equiv \left[L_{iFk}^{\frac{\sigma-1}{\sigma}} + \zeta M_{iFk}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{16}$$

When $\beta_K = 0$ the production function reduces to the standard form $q_{iFk} = z_{iFk}\, \Psi_{iFk}$. Operating capital more intensively incurs a convex utilization cost, capturing energy, maintenance, and depreciation expenditures (Greenwood et al., 1988):

$$\Phi(u_{iFk}) = \phi\, \frac{u_{iFk}^{\delta}}{\delta}, \qquad \phi > 0,\ \delta > 1 \tag{17}$$

This cost represents expenditure that leaves the local economy and is subtracted from operating profits. With

$$L_{iFk} = L_{inFk} + \vartheta L_{imFk} \tag{18}$$

Where L_{iFk} is a labor composite in which firms decide how many natives L_{inFk} and migrants L_{imFk} to hire. Additionally, M_{iFk} indicates the amount of materials or intermediate inputs firms hire, and u_{iFk} is the rate at which installed capital is utilized.

Firms' problem: In the labor market, firms are symmetric from workers' perspective and post the same wage schedule for each worker type j within market k. As a result, each firm faces an upward-sloping labor supply curve and the market is oligopsonistic. Firms face an increasing and convex expected cost to hire informal workers which can differ across workers' types: $\tau_{ij}\left(\mathbf{L_j}\right)$ with $\tau'_{ij} > 0$ and $\tau''_{ij} > 0$ where $j \in \{n, m\}$. Hiring workers formally entails a payroll tax τ_W, which is constant and equal for migrants and natives. If informal hiring is less costly for migrants than for natives ($\tau_{in} > \tau_{im}$), then firms optimally hire migrants informally more often, implying a higher informality rate among migrants.

Based on this, firms will hire (L_{inFk}, L_{imFk}) and the cost to hire informally both type of workers is going to determine a value $\mathbf{L_n}$, $\mathbf{L_m}$ from which firms are going to hire formal workers. Then they will hire $\mathbf{L_j}$ informal workers and $L_{ijFk} - \mathbf{L_j}$ formal workers. Given this setting it is expected that $\mathbf{L_n} < \mathbf{L_m}$ indicating a higher proportion of informal workers hired among migrants.

Given that the EAM and the empirical analysis focus on firms with more than ten employees, all firms are assumed to employ at least a fraction of workers formally, particularly among natives. Accordingly, two cases are relevant. First, firms may hire all migrant workers informally while employing a mix of formal and informal native workers. Second, firms may hire both migrants and natives using a combination of formal and informal contracts. In either case, firms maximize profits given by:

$$\max_{\{L_{niFk}, L_{miFk}, u_{iFk}\}} \Pi_{iFk} = p_{iFk}\left(q_{iFk}\right) q_{iFk} - \mathrm{Y}_{iFk}\left(L_{inFk}, L_{imFk}, M_{iFk}\right) - \Phi(u_{iFk}) \tag{19}$$

Subject to (15) and (18). Where the cost function is given by:

$$\mathrm{Y}_{iFk} = \begin{cases} \tau_{in}(\mathbf{L_n})\, w_{nFk} + (1+\tau_W)\, w_{nFk}(L_{inFk} - \mathbf{L_n}) + \tau_{im}(L_{imFk})\, w_{mFk} + p_M M_{iFk}, & \text{if } L_{inFk} > \mathbf{L_n},\ L_{imFk} < \mathbf{L_m}, \\ \sum\limits_{j\in\{n,m\}} \Big(\tau_{ij}(\mathbf{L_j})\, w_{jFk} + (1+\tau_W)\, w_{jFk}(L_{ijFk} - \mathbf{L_j})\Big) + p_M M_{iFk}, & \text{if } L_{ijFk} > \mathbf{L_j} \text{ for } j \in \{n,m\}. \end{cases} \tag{20}$$

Where the first part corresponds to case (i) and the second part to case (ii) explained above. As can be seen when firms hire workers formally then the cost of doing that is equal to $(1+\tau_W)w_{jFk}$ where τ_W is the payroll tax firms have to pay. On the other hand, the (expected) cost of informal hiring for type j is $\tau_{ij}(\mathbf{Lj})w_{jFk}$. Here we also have that $\mathbf{L_j}$ is the number of informal workers firms are going to hire and $L_{ijFk} - \mathbf{L_j} = L^f_{ijFk}$ is the number of formal workers they will hire of each type. Conditional on the effective labor cost (which incorporates the optimal mix of formal and informal contracts), the firm's cost-minimization problem proceeds in two stages. In the inner stage, the firm minimizes the cost of the labor–materials composite:

$$\min_{L_{iFk},\, M_{iFk}} w_{Fk}\left(L_{iFk}\right) L_{iFk} + p_M M_{iFk} \tag{21}$$

Subject to (16) and (18). This inner problem determines the optimal mix of labor and materials for a given level of Ψ_{iFk}, yielding the unit composite cost W_k. In the outer stage, the firm jointly determines the CES composite and utilization by minimizing total variable cost:

$$\min_{u_{iFk},\, \Psi_{iFk}} W_k\, \Psi_{iFk} + \Phi(u_{iFk}) \qquad \text{s.t.} \quad q_{iFk} = z_{iFk}\, u_{iFk}^{\beta_K}\, \Psi_{iFk}^{1-\beta_K} \tag{22}$$

When $\beta_K = 0$, the outer stage is trivial ($\Psi_{iFk} = q_{iFk}/z_{iFk}$, $\Phi = 0$) and the two-stage problem reduces to (21) alone. The conditional labor and intermediate inputs demands from the inner problem are given by:

$$L_{iFk} = \Psi_{iFk}\left[\frac{W_k}{(1+\tau_W)w_{Fk}}\right]^{\sigma} \tag{23}$$

$$M_{iFk} = \Psi_{iFk}\left[\frac{\zeta W_k}{p_M}\right]^{\sigma} \tag{24}$$

where, when $\beta_K = 0$, $\Psi_{iFk} = q_{iFk}/z_{iFk}$ and the original expressions are recovered. The unit cost of the labor–materials composite is $W_k = \left[(1+\tau_W)^{1-\sigma} w_{Fk}^{1-\sigma} + \zeta^{\sigma}\, p_M^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$. The marginal cost of output,

obtained from the envelope theorem on the outer problem (22), is

$$\mathbf{MC}_{iFk} = \frac{W_k \, \Psi_{iFk}}{(1 - \beta_K) \, q_{iFk}} \tag{25}$$

which reduces to $\mathbf{MC} = W_k / z_{iFk}$ when $\beta_K = 0$. Because marginal cost now depends on output through optimal utilization, the pricing and output decisions are jointly determined.

The first-order condition for utilization from the outer problem (22) equates the shadow value of capacity services to their marginal cost:

$$\frac{\beta_K \, \mathbf{MC}_{iFk} \, q_{iFk}}{u_{iFk}} = \phi \, u_{iFk}^{\delta - 1} \tag{26}$$

Higher firm-level output raises optimal utilization. This creates a channel through which a migration-driven expansion in output raises u^*_{iFk}, which in turn increases the marginal product of labor:

$$\text{MPL}_{iFk} = \vartheta \, (1 - \beta_K) \, \theta_{L,iFk} \, \frac{q_{iFk}}{L^{\text{eff}}_{iFk}} \tag{27}$$

where $\theta_{L,iFk} = \frac{L_{iFk}^{(\sigma-1)/\sigma}}{L_{iFk}^{(\sigma-1)/\sigma} + \zeta \, M_{iFk}^{(\sigma-1)/\sigma}}$ is the CES labor share and $L^{\text{eff}}_{iFk} = L_{inFk} + \vartheta \, L_{imFk}$ is effective labor. Based on these expressions, the profit maximization problem over output is given by:

$$\max_{q_{iFk}} \Pi_{iFk} = p_{iFk} \left(q_{iFk} \right) q_{iFk} - W_k \, \Psi_{iFk} - \Phi(u^*_{iFk}) \tag{28}$$

This yields the optimal price $p_{iFk} = \mu_{iFk} \, \mathbf{MC}_{iFk}$, which, combined with the utilization condition (26), jointly pins down q_{iFk} and u^*_{iFk}. Once we have q_{iFk} we can obtain L_{iFk} and M_{iFk}. This would give us the value of w_{Fk} which from the labor cost minimization between natives and migrants subject to (18), should meet the following conditions:

$$(1 + \tau_W) w_{nFk} \nu_{inFk} = w_{Fk} \qquad (1 + \tau_W) w_{mFk} \nu_{imFk} = \vartheta w_{Fk} \tag{29}$$

And then based on the labor supply of both groups we can pin down the optimal L_{inFk} and L_{imFk}. To obtain the total labor force of each type hired by the firms we need to find the thresholds $\mathbf{L_n}$, $\mathbf{L_m}$ which are going to be given by the point at which the marginal cost of hiring an informal worker is equal to the marginal cost of hiring a formal worker. The marginal cost of hiring formal workers is given by $(1 + \tau_W) \, w_{jFk}$, and the marginal cost of hiring informal workers is given by $\tau'_{ij} w_{jFk}$. Then the threshold is going to be given by the point at which

$$(1 + \tau_W) = \tau'_{ij} \tag{30}$$

From this expression, given that the cost of hiring migrants as informal workers is significantly lower, the share of informal wage-workers in the firm sector for migrants is going to be significantly higher compared to natives for a given cost of hiring formal workers.

Characterization - Markups: From the FOC of consumers

$$c_{ijFk} = \beta_j^{\rho_j} \left(\frac{p_{iFk}}{P_{jFk}}\right)^{-\eta_j} \left(\frac{P_{jFk}}{P_{jk}}\right)^{-\rho_j} C_{jk} \tag{31}$$

Then, the elasticity of the demand for consumers j will be given by

$$\varepsilon^D_{ijFk} = \frac{\partial \ln\left(c_{ijFk}\right)}{\partial \ln\left(p_{iFk}\right)} = \left[\frac{1}{\eta_j}\left(1 - s_{ijFk}\right) + \frac{1}{\rho_j} s_{ijFk}\right]^{-1} \qquad \text{where,} \qquad s_{ijFk} = \frac{p_{iFk} c_{ijFk}}{P_{jFk} C_{jFk}} \tag{32}$$

Then, when firm i is small ($s_{ijFk} \to 0$), demand elasticity approaches η_j; when firm i becomes large, elasticity approaches ρ_j. We know that the total demand of the firm is given by $Q^D_{iFk} = \sum_j c_{ijFk}\left(p_{iFk}\right)$. Then, given $\Omega_{ijFk} = c_{ijFk} / \left(c_{inFk} + c_{imFk}\right)$, firm i markup is given by

$$\mu_{iFk} = \frac{\varepsilon^D_{iFk}}{\varepsilon^D_{iFk} - 1} \quad \text{where} \quad \varepsilon^D_{iFk} = \sum_j \Omega_{ijFk} \left[\frac{1}{\eta_j}\left(1 - s_{ijFk}\right) + \frac{1}{\rho_j} s_{ijFk}\right]^{-1} \tag{33}$$

This final equation provides a rationale for the negative effect on markups observed in the empirical analysis following the migration shock. As migrants enter the country, firms increasingly sell their products to migrant consumers, which raises the value of Ω_{imFk} for each firm. Because migrants are assumed to be more sensitive to price changes—substituting more intensively both across firms and across sectors relative to natives—their demand elasticity satisfies $\varepsilon^D_{imFk} > \varepsilon^D_{inFk}$. As a result, the weighted average demand elasticity ε^D_{iFk} increases in absolute value, reducing the markups that firms are able to charge in the local market.

Characterization - Markdowns: Define χ_{ijFk} as the labor supply elasticity of workers j faced by firm i, and χ_{iFk} as the labor market k labor supply elasticity of sector F. Then, the markdown for firms F imposed on workers j is given by

$$\nu_{ijFk} = \left[1 + \frac{1}{\chi_{ijFk}}\right] \tag{34}$$

We know that the optimal wage paid by the firms F to employees $j \in \{n, m\}$ is given by $w^*_{jFk} = w^*_{jFk}\left(L_{jFk}\left(L_{ijFk}\right)\right)$. Which implies that the optimal wage paid by the firms depends on the total supply in the local labor market of worker type j to the sector F which at the same time depend on the individual supply faced by each firm. Then

$$\frac{\partial w_{jFk}}{\partial L_{ijFk}} \frac{L_{ijFk}}{w_{jFk}} = \frac{s^N_{ijFk}}{\chi_{jFk}} \to \frac{1}{\chi_{ijFk}} = \frac{s^N_{ijFk}}{\chi_{jFk}} \tag{35}$$

Where $s^N_{ijFk} \equiv \frac{L_{ijFk}}{L_{jFk}}$ is the share of workers j hired by firm i in sector F relative to the total employment of j in sector F and local labor market k. Then, the markdown charged by firm i is

$$\nu_{ijFk} = \frac{s^N_{ijFk}}{\chi_{jFk}} + 1 \tag{36}$$

This wage markdown equation implies that the ratio of the marginal productivity of labor to the wage paid by firm i increases with the firm's employment share in the local labor market, but decreases with the elasticity of labor supply in that market.

Characterization - Labor supply elasticities: The supply of workers j in the firm sector F is

$$L^s_{jFk} = \frac{\left(w_{jFk}\right)^{\theta_j}}{\left(w_{jFk}\right)^{\theta_j} + \left(w_{Sk}\right)^{\theta_j}} N_{jk} \tag{37}$$

Then, defining $\chi_{jFk} \equiv \frac{\partial L^s_{jFk}}{\partial w_{jFk}} \frac{w_{jFk}}{L^s_{jFk}}$, we have that the local labor market k labor supply elasticity to the firm sector is given by

$$\chi_{jFk} = \frac{\theta_j \left(w_{Sk}\right)^{\theta_j}}{\left[\left(w_{jFk}\right)^{\theta_j} + \left(w_{Sk}\right)^{\theta_j}\right]} = \theta_j \Xi_{jSk} \rightarrow \chi_{jFk} = \theta_j \Xi_{jSk} \tag{38}$$

Where Ξ_{jSk} is the proportion of workers j working in sector S in the local labor market k. Then the markdowns imposed on natives and migrants by firm i in the firm sector are given by:

$$\nu_{inFk} = \frac{s^N_{inFk}}{\theta_n \Xi_{nSk}} + 1 \qquad \nu_{imFk} = \frac{s^N_{imFk}}{\theta_m \Xi_{mSk}} + 1 \tag{39}$$

This result is similar to the main result of Amodio et al. (2025), which suggests that the labor market power of firms in the wage sector is going to depend negatively on the attractiveness of the self-employment sector, but also on the relative elasticity between the self-employment sector and the firm-sector. This implies that the average markdown imposed by firm i on its workforce is:

$$\overline{\nu}_{iFk} = \varsigma^F_{in} \left[\frac{s^n_{iFk}}{\theta_n \Xi_{nSk}} + 1\right] + \left(1 - \varsigma^F_{in}\right) \left[\frac{s^m_{iFk}}{\theta_m \Xi_{mSk}} + 1\right] \tag{40}$$

where $\varsigma^F_{in} = \frac{L_{inFk}}{L_{iFk}}$ denotes the share of natives in firm i's workforce in the firm sector. This final expression clarifies the main channels through which a migration shock affects the average markdown imposed by firms.

First, by reducing the value of self-employment—and thus its attractiveness for natives, captured by a decline in Ξ_{nSk}—the migration shock increases the markdown that firms can impose on native workers. Second, by raising migrant employment within firms, the share of natives in total firm employment, ς^F_{in}, declines, placing greater weight on the markdown imposed on migrants in the firm-level average. Because migrants also exhibit a lower elasticity of substitution between firm employment and self-employment, θ_m, firms hold greater monopsony power over migrant workers than over natives, all else equal. Together, these forces increase the average markdown that firms impose on their workforce following the migration shock, partially offsetting productivity gains and the effects of reduced price markups induced by the exodus.

10.2 Firm Entry

Productivity and potential entrants. In each local labor market k, potential entrants in the firm sector arrive according to a Poisson distribution with mean $\mathbb{E}(M_k^*) = \bar{M}_k^*$. Each potential entrant independently draws productivity z from a Pareto distribution with lower bound $\underline{z}_k$ and shape parameter θ:

$$G_k(z) = 1 - \left(\frac{\underline{z}_k}{z}\right)^{\theta}, \qquad z \geq \underline{z}_k. \tag{41}$$

Under this Poisson–Pareto structure, the parameter $T_k \equiv \bar{M}_k^* \underline{z}_k^{\theta}$ is a sufficient statistic for expected productivity in market k (Gaubert and Itskhoki, 2021), provided the least productive firms do not enter. To capture cross-market heterogeneity, I assume

$$T_k \sim \log \mathcal{N}(\mu_T, \sigma_T^2). \tag{42}$$

Entry and cutoff. Firms must pay a fixed entry cost $f^e(n_k)$ (in units of the final good). After observing productivity, a firm enters if and only if profits are non-negative. There exists a cutoff productivity z_k^* such that $\pi_{iFk}(z_k^*) = 0$. Only firms with $z \geq z_k^*$ operate. The expected mass of active firms in market k is

$$M_k = \bar{M}_k^* \left(\frac{\underline{z}_k}{z_k^*}\right)^{\theta}. \tag{43}$$

At the entry stage, firms behave atomistically and anticipate the "small-firm" (limit) markup μ_k^A implied by $s_{ijFk} \to 0$ in (33). Using the anticipated pricing rule $p_k(z) = \mu_k^A \, \mathbf{MC}_k(z)$ and the optimal utilization from (26), anticipated operating profits equal $p_k(z)\, q_k(z) - W_k\, \Psi_k(z) - \Phi(u_k^*(z))$. Free entry implies that the marginal entrant earns zero profits:

$$p_k(z_k^*)\, q_k(z_k^*) - W_k\, \Psi_k(z_k^*) - \Phi\big(u_k^*(z_k^*)\big) = f^e(n_k) \tag{44}$$

When $\beta_K = 0$, $\Phi = 0$ and $W_k \Psi_k = \frac{W_k}{z_k^*} q_k$, so this reduces to $(\mu_k^A - 1)\frac{W_k}{z_k^*} q_k(z_k^*) = f^e(n_k)$. In the production stage, realized markups are firm-specific, μ_{iFk}, because they depend on equilibrium market shares s_{ijFk} as in (33). This condition pins down z_k^* and therefore the equilibrium mass of firms M_k.

10.3 Equilibrium

An equilibrium in this economy is defined as a collection of wages $\{w_{jFk}, w_{Sk}\}_{j\in\{n,m\},\, k\in[0,1]}$, prices $\{p_M, p_{iFk}, P_{jFk}, P_{Sk}, P_{jk}\}$, quantities $\{L_{ijFk}, L_{jSk}, M_{iFk}, q_{iFk}, c_{ijFk}, u_{iFk}\}$, occupational choices $\{\Xi_{jFk}, \Xi_{jSk}\}$, markups $\{\mu_{iFk}\}_{k\in[0,1]}$, and markdowns $\{\nu_{ijFk}\}_{j\in\{n,m\},\, k\in[0,1]}$ such that:

1. **Household optimization.** Given prices, each worker of type $j \in \{n, m\}$ chooses between formal employment and self-employment, implying labor supply (11).

Consumption across goods produced in different markets is allocated according to α_{jk}, where $\int_0^1 \alpha_{jk} dk = 1$. So that a type-$j$ household residing in k' spends share α_{jk} of its income on goods produced in origin market k. Within each origin market k, consumption between the formal composite and self-employment good follows the nested CES structure given by (14), with price indices $P_{jFk} = \left(\sum_{i \in M_k} p_{iFk}^{1-\eta_j}\right)^{\frac{1}{1-\eta_j}}$ and $P_{jk} = \left(\beta_j^{\rho_j} P_{jFk}^{1-\rho_j} + P_{Sk}^{1-\rho_j}\right)^{\frac{1}{1-\rho_j}}$.

2. **Formal firms.** Each firm $i \in M_k$ minimizes cost subject to (15) and (18), and chooses utilization optimally according to (26), implying marginal cost $MC_{iFk} = W_k \Psi_{iFk} / [(1-\beta_K) q_{iFk}]$, where W_k is the unit cost of the labor-material composite. Prices satisfy the markup condition $p_{iFk} = \mu_{iFk} MC_{iFk}$. Labor composition satisfies (29), (36), and (38).

3. **Self-employment sector.** Self-employment production is linear $Q_{Sk} = L_{Sk} \equiv \sum_{j \in \{n,m\}} L_{jSk}$ and (P_{Sk}, w_{Sk}) satisfy zero profit.

4. **Market clearing.**

   Labor markets: $L_{jFk}^s = \sum_{i \in M_k} L_{ijFk}^D$ and $L_{Sk}^s = L_{Sk}^D$.

   Goods markets: Let $C_{jSk}(k')$ and $c_{ijFk}(k')$ denote consumption by residents of market k' of goods produced in origin market k. For each origin market k, $Q_{Sk} = \sum_{k'} \sum_{j \in \{n,m\}} C_{jSk}(k')$ and $q_{iFk} = \sum_{k'} \sum_{j \in \{n,m\}} c_{ijFk}(k')$. That is, supply equals total demand aggregated across all residence markets k'.

5. **Income and profit rebating.** Household income in market k satisfies $I_{jk'} = w_{jFk'} L_{jFk'} + w_{Sk'} L_{jSk'} + \Pi_{jk'}$, where total formal profits generated in market k,

$$\Pi_k = \sum_{i \in M_k} [p_{iFk} q_{iFk} - W_k \Psi_{iFk} - \Phi(u_{iFk}^*)] - f^e$$

   are rebated lump-sum to native residents of market k.

6. **Firm entry.** For each market k, productivity cutoff z_k^* satisfies $p_k(z_k^*) q_k(z_k^*) - W_k \Psi_k(z_k^*) - \Phi(u_k^*(z_k^*)) = f^e(n_k)$, and the mass of firms equals $M_k = \bar{M}_k^* \left(\frac{z_k}{z_k^*}\right)^\theta$.

11 Estimation

11.1 Parameterization

Informality costs. Following Ulyssea (2018), I parameterize the expected cost of hiring informal workers of type $j \in \{n, m\}$ by firm i as a convex function of informal employment:

$$\tau_{ij}(l_{ij}) = \left(1 + \frac{l_{ij}}{b_{ij}}\right) l_{ij}, \qquad b_{ij} > 0, \tag{45}$$

where l_{ij} denotes the number of informal workers of type j hired by firm i. This specification implies that the marginal cost of informality is increasing in the number of informal workers, capturing

rising detection probabilities, enforcement risk, or organizational frictions as informal employment expands. The parameter b_{ij} governs the curvature of the informality cost schedule: smaller values of b_{ij} imply faster growth of marginal costs and therefore a lower optimal level of informality. Allowing $b_{im} > b_{in}$ captures the idea that informality is less costly for migrants than for natives, rationalizing higher equilibrium informality rates among migrant workers.

Entry costs. I allow fixed entry costs to vary with the order of entry within a local labor market. Let n denote the rank of a potential entrant, ordered by productivity. The fixed cost associated with the n-th entrant is given by

$$f^e(n) = \begin{cases} 0 & \text{if } n = 1, \\ f_0 + f_1\sqrt{n} & \text{if } n \geq 2, \end{cases} \tag{46}$$

with $f_0, f_1 > 0$. Assigning zero entry cost to the first entrant guarantees that production takes place in every local labor market. Allowing fixed costs to rise with the number of active firms introduces increasing difficulty of entry as markets become more crowded. Under the Poisson–Pareto productivity structure, this feature ensures that the equilibrium productivity cutoff remains strictly above the lower bound $\underline{z}_k$, preventing marginal low-productivity draws from becoming active and preserving the role of T_k as a summary measure of market-level productivity.

Capacity utilization. The utilization parameters (β_K, δ, ϕ) are calibrated rather than estimated. The capital-intensity parameter β_K is set to 0.15, consistent with the capital share in Colombian manufacturing after netting out materials. The convexity parameter $\delta = 2$ yields a quadratic cost of utilization, and the cost level ϕ is calibrated so that mean utilization equals 0.80 in the pre-migration baseline.

12 Final Remarks

This paper studies the wage effects of migration in a setting where firms possess market power in both labor and product markets. Exploiting the Venezuelan exodus to Colombia as a large and plausibly exogenous migration shock, I show that migration increased firm employment, output, and the marginal productivity of labor in the Colombian manufacturing sector, yet left average wages unchanged. This pattern cannot be reconciled within a competitive framework in which wages fully reflect marginal productivity.

I interpret these findings through a non-competitive lens in which wages depend not only on productivity but also on firms' wage markdowns and price markups. On the labor market side, I document that migration increased firms' labor market power by raising wage markdowns. I argue that this adjustment was driven by a decline in the value of self-employment, which serves as a key outside option for manufacturing workers in developing economies. As migrant inflows disproportionately expanded self-employment—often due to limited access to formal employment—

competition in that sector increased, reducing its attractiveness and strengthening firms' monopsony power over wage workers. On the product market side, I show that migration shifted the composition of local demand toward more price-sensitive consumers, reducing firms' price markups. Together, these adjustments muted the pass-through of productivity gains into wages.

To rationalize these empirical patterns, I develop a tractable general equilibrium model with imperfect competition in both labor and product markets. In the model, heterogeneous native and migrant workers self-select between wage employment and self-employment, which disciplines firms' wage-setting behavior and links labor market power to the attractiveness of outside options. The model also incorporates an intensive formal–informal hiring margin, allowing firms to trade off payroll taxes against convex expected costs of informal employment that differ by worker type. This margin captures empirically relevant heterogeneity in informality rates and provides an additional channel through which firms can absorb productivity gains generated by migrant workers. On the demand side, native and migrant consumers differ in their elasticities of substitution across varieties and sectors, so that migration alters the effective demand elasticity faced by firms and, in turn, their optimal price markups.

In the medium run, productivity gains are absorbed through adjustments in labor and product market power, increasing profitability and entry without raising wages. These results highlight that understanding the wage effects of migration requires jointly accounting for labor and product market power, as well as the structure of outside options and informality in host economies. Ignoring any of these margins can lead to misleading conclusions about how migration affects wages, profits, and welfare. By clarifying these mechanisms, this paper contributes to a more complete framework for evaluating migration policy, labor market regulation, and competition policy in both developing and developed countries.

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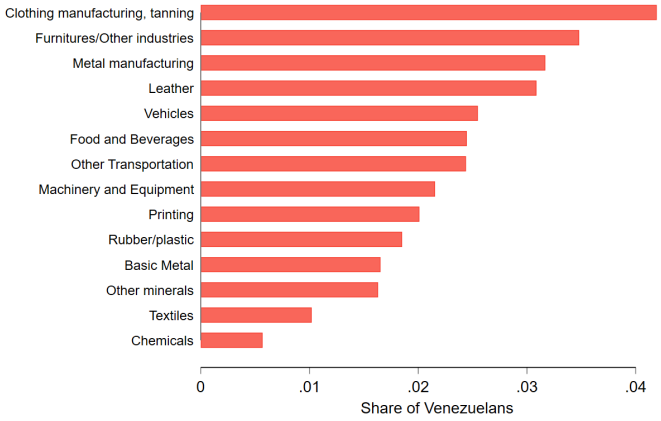
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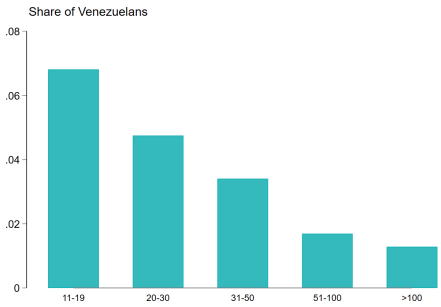
A Appendix: Tables and Figures

Figure A.1: Share of Venezuelans relative to Colombians, 2019

(a) By 2-digit Industry



(b) by Firm-size



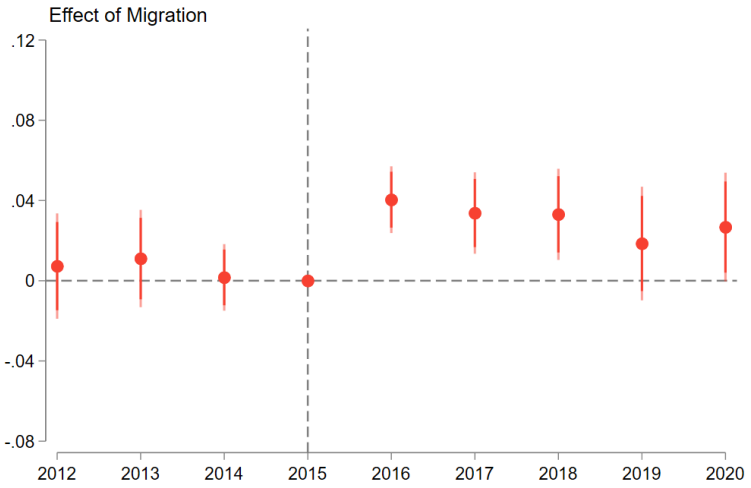
Notes: Venezuelan immigrants are defined as individuals born in Venezuela. Each share in the figure is computed as the ratio of Venezuelans to Colombians working in the manufacturing sector, restricting the sample to municipalities covered by the EAM and to firms with 10 or more employees, within each corresponding category. Source: Own elaboration based on GEIH data from DANE.

Table A.1: First Stage

	(1)	(2)
Inverse Distance	156.98***	147.42***
	(11.53)	(13.00)
F-statistic	185.5	128.61
Number of Municipalities	124	120
Observations	3,800	3,794
Industry FE	Yes	Yes
LLM Controls	No	Yes

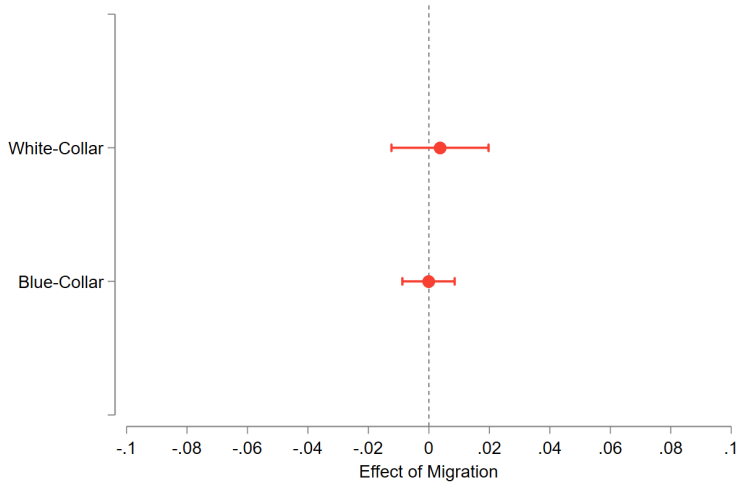
Notes: The coefficients represent the estimation of the interaction between the main independent variable and a dummy variable that takes a value of 1 for observations from years between 2016 and 2020, pooling all years in the sample, according to equation 6. Industry fixed effects are specified at the 4-digit CIIU level. Local Labor Market (LLM) controls include the variables specified in Section 5.2. Kleibergen-Paap rk Wald F-statistics is provided. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively. Source: Own elaboration based on data from DANE.

Figure A.2: Impact of the Venezuelan exodus on the Average Product Per Worker, 2012-2020



Notes. The estimates include Industry fixed effects at the 4-digit CIIU level. They also control for the Local Labor Market (LLM) controls specified in Section 5.2. The bars represent the 95% (light bars) and 90% (darker bars) confidence intervals. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

Figure A.3: Impact of the Venezuelan exodus on Average Wages by Employment Category, 2012-2020



Notes. For each employment group, the coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. The estimates include Industry fixed effects at the 4-digit CIIU level. They also control for the Local Labor Market (LLM) controls specified in Section 5.2. The bars represent the 95% (light bars) and 90% (darker bars) confidence intervals. Standard errors are clustered at the level of the local labor market level. Source: Own estimates based on EAM data from DANE.

Table A.2: Heterogeneous Effects on Labor Market Outcomes

	Markdown (in logs)		MPL (in logs)	
	Full sample	No exposure	Full sample	High exposure
Share of migrants	0.059***	0.043**	0.032***	0.086**
	(0.009)	(0.017)	(0.006)	(0.034)
F-statistics	58.52	73.606	59.23	109.578
Observations	26,299	13,017	26,397	1,280
Industry FE × Year FE	Yes	Yes	Yes	Yes
LLM Controls × Year FE	Yes	Yes	Yes	Yes

Notes: The coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. To measure exposure to Venezuelan participation in the manufacturing sector, I use GEIH data to compute, for each four-digit industry and local labor market, the share of Venezuelan workers in the total labor force over the post-exodus period. This share is then imputed to all firms operating in the same industry-local-labor-market cell. Firms with zero imputed exposure are classified as no-exposure firms. High-exposure firms are defined as those in the top five percent of the imputed exposure distribution across the full sample. Industry fixed effects are specified at the 4-digit CIIU level. Local Labor Market (LLM) controls include the variables specified in Section 5.2. Kleibergen-Paap rk Wald F-statistics is provided. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

Table A.3: Heterogeneous Effects on Output Market Outcomes

	Markup (in logs)	
	Non-exporter	Exporter
Share of migrants	-0.034***	0.023
	(0.008)	(0.031)
F-statistics	43.27	71.44
Observations	16,578	9,665
Industry FE × Year FE	Yes	Yes
LLM Controls × Year FE	Yes	Yes

Notes: The coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. Exporter firms are defined as those whose average share of exported goods relative to total output lies in the top third of the across-firm distribution. Non-exporters correspond to firms in the bottom two thirds of this distribution. Industry fixed effects are specified at the 4-digit CIIU level. Local Labor Market (LLM) controls include the variables specified in Section 5.2. Kleibergen-Paap rk Wald F-statistics is provided. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

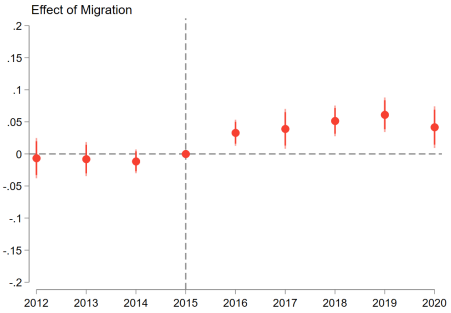
Table A.4: Heterogeneous Effects on Output Market Outcomes

	Output	MPL	Labor
Panel A: Market Scope			
Local			
Share of migrants	0.060***	0.039***	0.032***
	(0.014)	(0.009)	(0.010)
F-statistics	60.46	60.02	60.46
Observations	11,436	10,595	11,436
Non-local			
Share of migrants	-0.005	0.020	-0.038
	(0.039)	(0.032)	(0.027)
F-statistics	38.36	53.99	38.36
Observations	7,636	7,332	7,636
Panel B: Capacity Utilization			
Low			
Share of migrants	0.053***	0.033***	0.027**
	(0.013)	(0.009)	(0.011)
F-statistics	65.74	64.90	65.74
Observations	11,533	10,673	11,533
High			
Share of migrants	0.015	0.002	-0.008
	(0.051)	(0.025)	(0.042)
F-statistics	30.58	28.43	30.58
Observations	7,387	7,060	7,387
Industry FE × Year FE	Yes	Yes	Yes
LLM Controls × Year FE	Yes	Yes	Yes

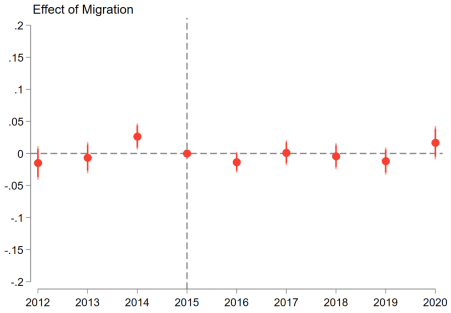
Notes: The coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. Firms relying on local markets are defined as those whose share of transportation costs related to the sale of their products relative to output is below the mean of this share among firms in the same department and four-digit industry, while firms not relying on local markets are those with transportation cost shares above this mean. Industry fixed effects are specified at the 4-digit CIIU level. Local Labor Market (LLM) controls include the variables specified in Section 5.2. Kleibergen-Paap rk Wald F-statistics is provided. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

Figure A.4: Effect on Capacity Utilization, 2012-2020

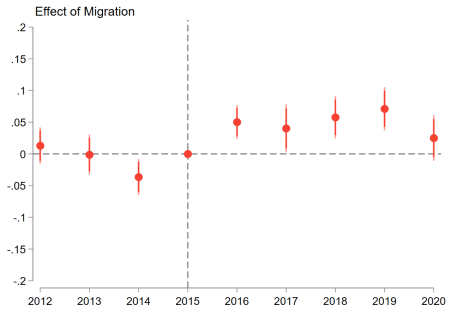
(a) Effect on Energy Utilization



(b) Effect on Capital



(c) Effect on Energy/Capital



Notes. The estimates include Industry fixed effects at the 4-digit CIIU level. They also control for the Local Labor Market (LLM) controls specified in Section 5.2. The bars represent the 95% (light bars) and 90% (darker bars) confidence intervals. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

B Appendix: Robustness Exercises

Table B.1: Robustness Checks: Markup Effects for Single-Product and Homogeneous-Good Firms

	Markup (in logs)	
	Single-product	Homogeneous-good
Share of migrants	-0.030*	-0.078*
	(0.015)	(0.051)
F-statistics	14.70	19.99
Observations	5,952	610
Industry FE × Year FE	Yes	Yes
LLM Controls × Year FE	Yes	Yes

Notes: The coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. Single-product firms are defined as those producing only one 7-digit product based on the CPC v2. classification from DANE during the baseline period. Homogeneous-good firms are defined as those whose more than the 75% of the total production value was represented by homogeneous products. The following 3-digit CPC products were considered homogeneous: hard coal, lignite, and peat; limestone, gypsum, and other calcareous stone used in the manufacture of lime or cement; sand, gravel, crushed stone, and natural bitumen and asphalt; clays; coke and semi-coke of coal and retort carbon; refined petroleum oils and petroleum-based preparations; petroleum waxes, petroleum coke, bitumen, and other petroleum residues; gypsum, lime, and cement; worked building or monumental stone; basic iron and steel products; unwrought non-ferrous metals (copper, nickel, aluminum, lead, zinc, and tin); pure sodium chloride and its salts and sea water; refractory and structural clay products; and semi-finished products of non-ferrous metals and their alloys. Industry fixed effects are specified at the 4-digit CIIU level. Local Labor Market (LLM) controls include the variables specified in Section 5.2. Kleibergen-Paap rk Wald F-statistics is provided. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

B.1 Alternative Production Functions

In the main specification considered in this paper, I used a 2-digit industry-specific second-order translog production function as follows:

$$y_{it} = \omega_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_e e_{it} + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{le} l_{it} e_{it} + ...$$

$$...\beta_{km} k_{it} m_{it} + \beta_{ke} k_{it} e_{it} + \beta_{me} m_{it} e_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{ee} e_{it}^2 + \varepsilon_{it}$$

where l, k, m, e are labor, capital, intermediate materials, and energy (all in logs), respectively.

y_{it} denotes the log of output for firm i in period t. The term ω_{it} captures the firm-level TFP and ε_{it} accounts for unobserved shocks specific to the firm and period.

Under this framework, the output elasticities—used for calculating wage markdowns and price markups—are not constant but depend on the levels of inputs utilized by the firms. This flexibility makes the second-order translog production function particularly suitable, as it is widely used in the economic literature for estimating firm wage markdowns and price markups via production function techniques (Yeh et al., 2022; Amodio et al., 2024; Estefan et al., 2024). Moreover, estimating the production function separately for each 2-digit industry ensures a high degree of flexibility, especially in estimating the coefficient vector (β). This approach enhances the model's capacity to capture industry-specific production dynamics.

Alternatively, I also re-estimate the production function using, first, the same second-order translog form assuming it is identical across all firms regardless of the sector to which they belong—which I will refer to as the homogeneous translog. Although this approach still allows output elasticities of inputs to vary across firms and over time, it imposes the restriction that the coefficient vector (β) is constant across the entire sample. Additionally, to test the robustness of my results, I consider a simpler production function: a Cobb-Douglas model estimated separately for each 2-digit industry in my sample, specified as follows:

$$y_{it} = \omega_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_e e_{it} + \varepsilon_{it}$$

Under the Cobb-Douglas production function, the marginal productivity of labor (MPL) is simply the average output per worker (APL) of the firm, scaled by the coefficient β_l of the production function, according to the following expression:

$$MPL_{it} = \beta_l \frac{Y_{it}}{L_{it}}$$

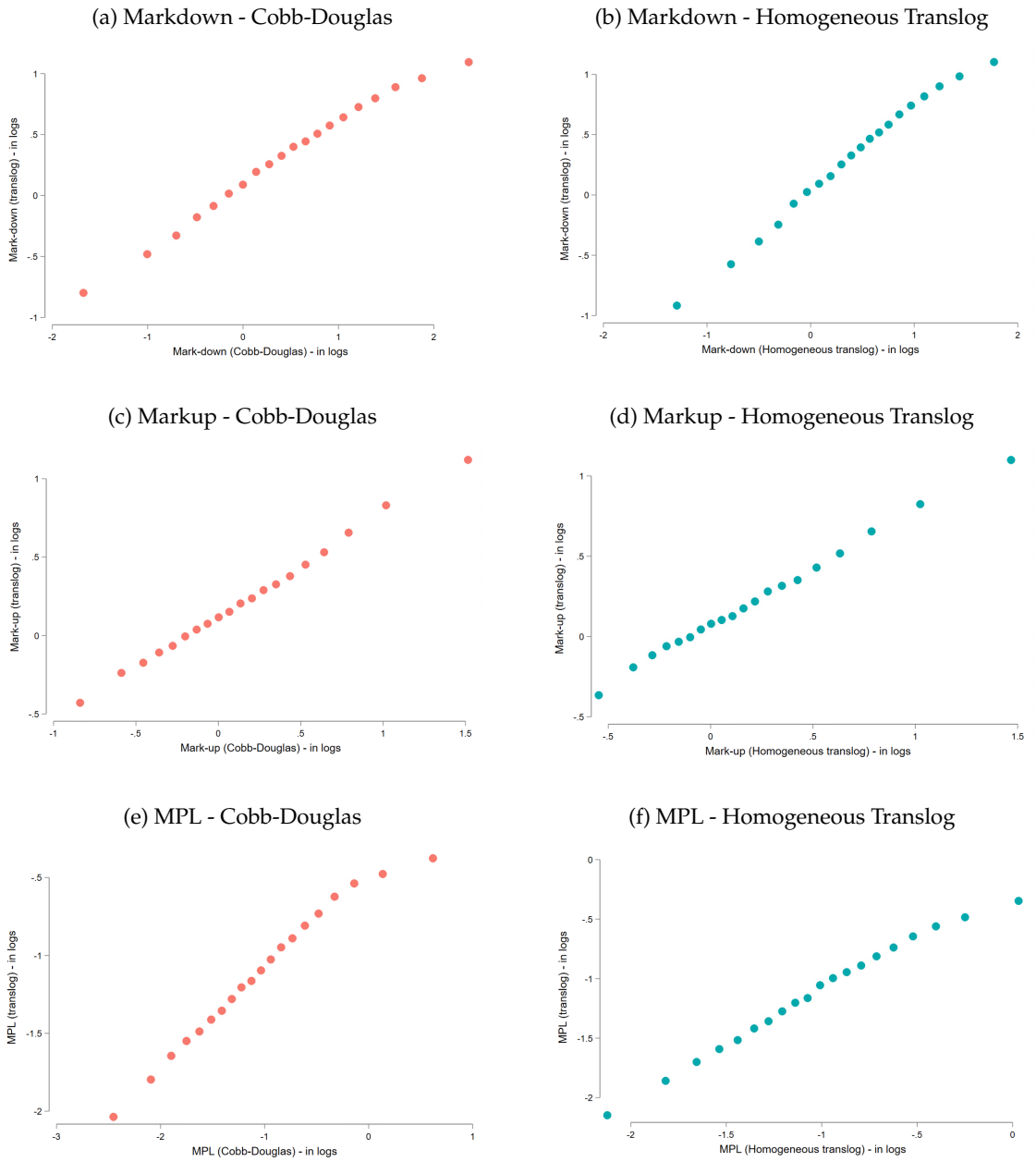
Where Y_{it} and L_{it} are the output and labor used by the firm, both in levels. Since β_l is constant over time, all variation in the MPL comes from the APL. Additionally, the wage markdown ν_{it} and the price markup μ_{it} are given by the following expressions:

$$\nu_{it} = \frac{\beta_l}{\beta_m} \frac{\alpha_{it}^m}{\alpha_{it}^l} \qquad \mu_{it} = \frac{\beta_m}{\alpha_{it}^m}$$

These simpler expressions imply that all the variation in the wage markdowns and the price markups will be primarily explained by the shares of labor and materials in the firms' revenues.

First, in Figure B.1, it can be observed that the measures of wage markdown, price markup, and marginal productivity of labor—derived using both the Cobb-Douglas production function and the Homogeneous Translog—are strongly correlated with those obtained using the main specification employed in the paper.

Figure B.1: Robustness exercise: Comparison of Firm Variables under Different Production Functions



Notes. The figures show the binscatter plot of the relationship between each corresponding variable (in logs) under different production functions. Source: Own estimates based on EAM data from DANE.

Additionally, when analyzing the effects on the MPL, wage markdown, and price markup using either of the two alternative production functions, the results in Table B.2 are very similar to the original estimates.

Table B.2: Robustness Exercise: Effect of Migration on Firm Outcomes under Different Production Functions

	MPL	Mark-down	Mark-up
Panel A: Homogeneous Translog			
Share of migrants	0.016***	0.050***	-0.027**
	(0.006)	(0.011)	(0.012)
F-statistic	62.47	58.99	54.52
Observations	26,499	26,447	26,629
	MPL	Mark-down	Mark-up
Panel B: Cobb-Douglas			
Share of migrants	0.028***	0.049***	-0.030***
	(0.006)	(0.010)	(0.011)
F-statistic	60.02	51.99	54.54
Observations	26,864	26,816	26,856
Industry FE × Year FE	Yes	Yes	Yes
LLM Controls × Year FE	Yes	Yes	Yes

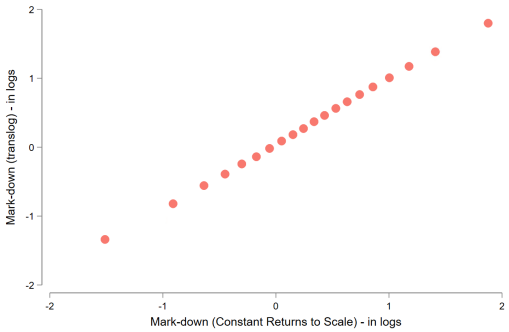
Notes: The coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. Industry fixed effects are specified at the 4-digit CIIU level. Local Labor Market (LLM) controls include the variables specified in Section 5.2. Kleibergen-Paap rk Wald F-statistics is provided. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

B.2 Constant Returns to Scale Production Function

When considering a second-order translog production function with constant returns to scale, it can be seen in Figure B.2 that the original measures of MPL, wage markdown, and price markups are strongly correlated with the new ones under this specific production function.

Figure B.2: Robustness exercise: Comparison of Firm Outcomes under Different Production Functions

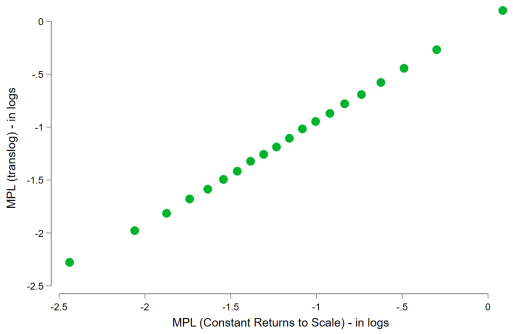
(a) Markdown - Constant Returns to Scale



(b) Markup - Constant Returns to Scale



(c) MPL - Constant Returns to Scale



Notes. The figures show the binscatter plot of the relationship between each corresponding variable (in logs) under different production functions. Source: Own estimates based on EAM data from DANE.

Additionally, in Table B.3 the results are very similar to the ones presented in the main specification.

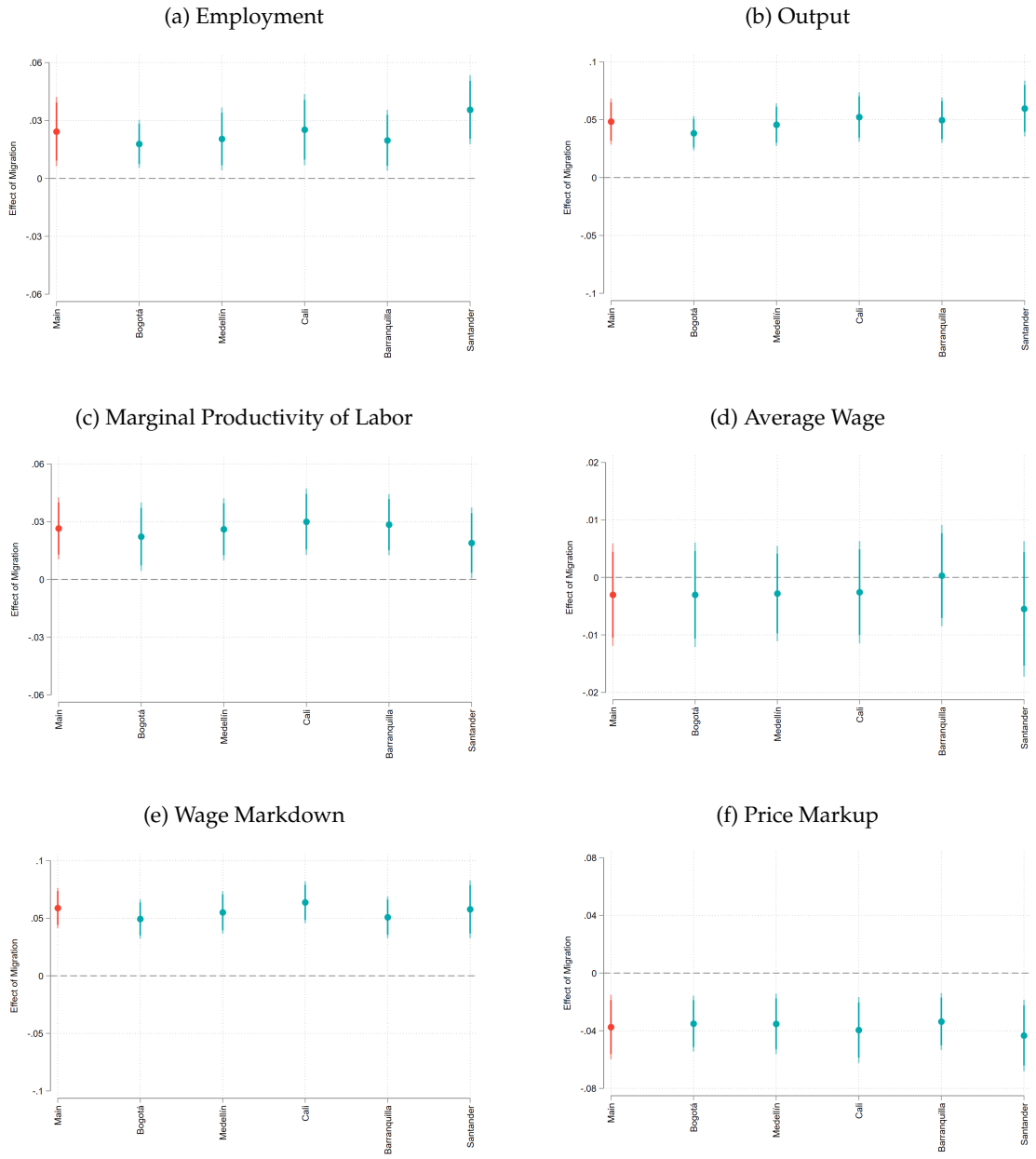
Table B.3: Robustness Exercise: Effect of Migration on Firm Outcomes - Constant Returns to Scale

	MPL	Mark-down	Mark-up
Share of migrants	0.031***	0.066***	-0.042***
	(0.008)	(0.010)	(0.007)
F-statistic	54.47	56.30	51.48
Observations	25,719	25,398	25,433
Industry FE × Year FE	Yes	Yes	Yes
LLM Controls × Year FE	Yes	Yes	Yes

Notes: The coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. Industry fixed effects are specified at the 4-digit CIIU level. Local Labor Market (LLM) controls include the variables specified in Section 5.2. Kleibergen-Paap rk Wald F-statistics is provided. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

B.3 Leave-one-out: Local Labor Markets

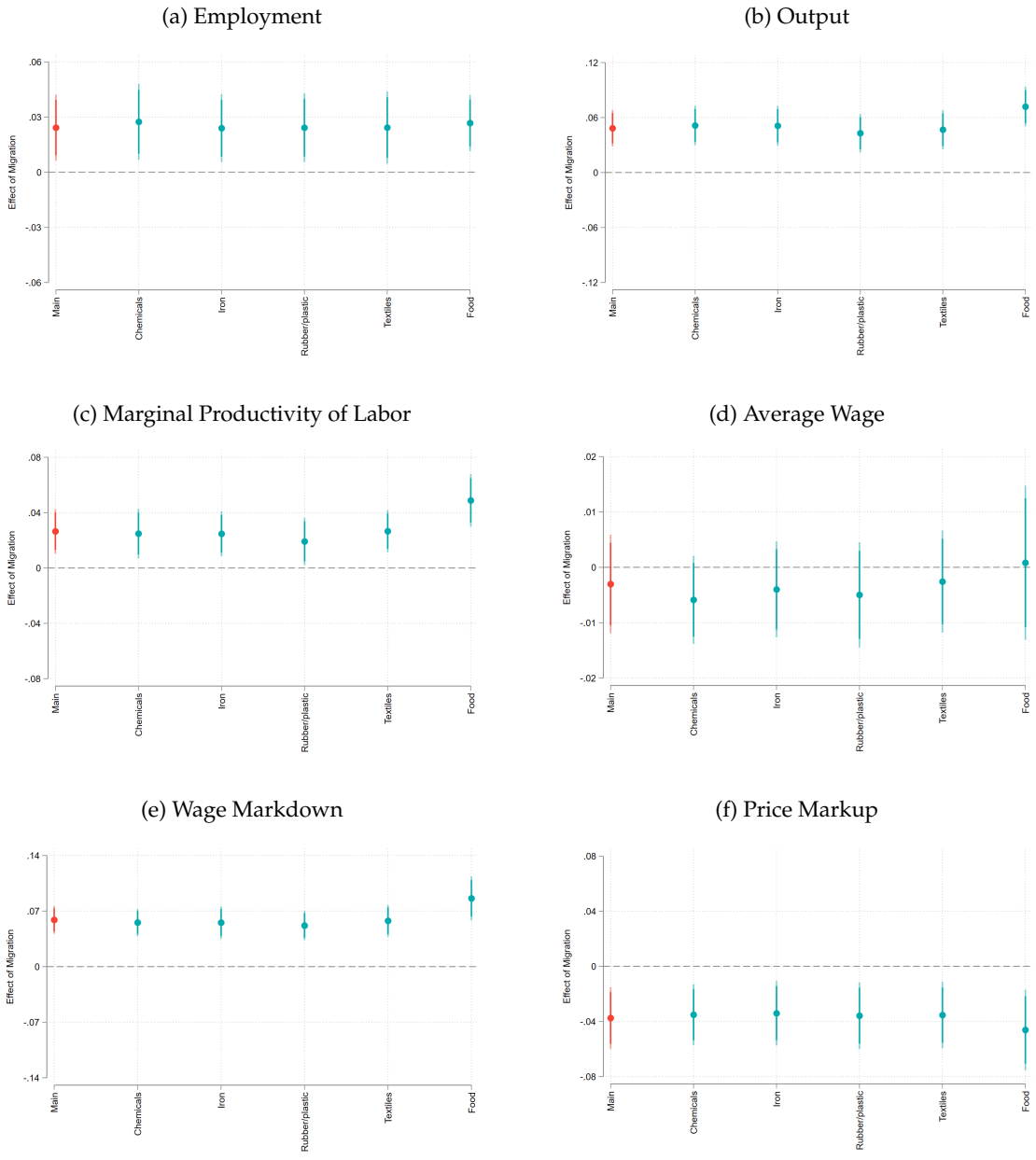
Figure B.3: Robustness exercise: Leave-one-out Top 5 Local Labor Markets, 2012-2020



Notes. The coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. The red coefficient indicates the original estimated effect of the migration shock on each respective outcome. The blue estimates correspond to the same effect but omit the local labor market specified on the x-axis. The estimates include Industry fixed effects at the 4-digit CIIU level. They also control for the Local Labor Market (LLM) variables specified in Section 5.2. The bars represent the 95% (light bars) and 90% (darker bars) confidence intervals. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

B.4 Leave-one-out: Industries

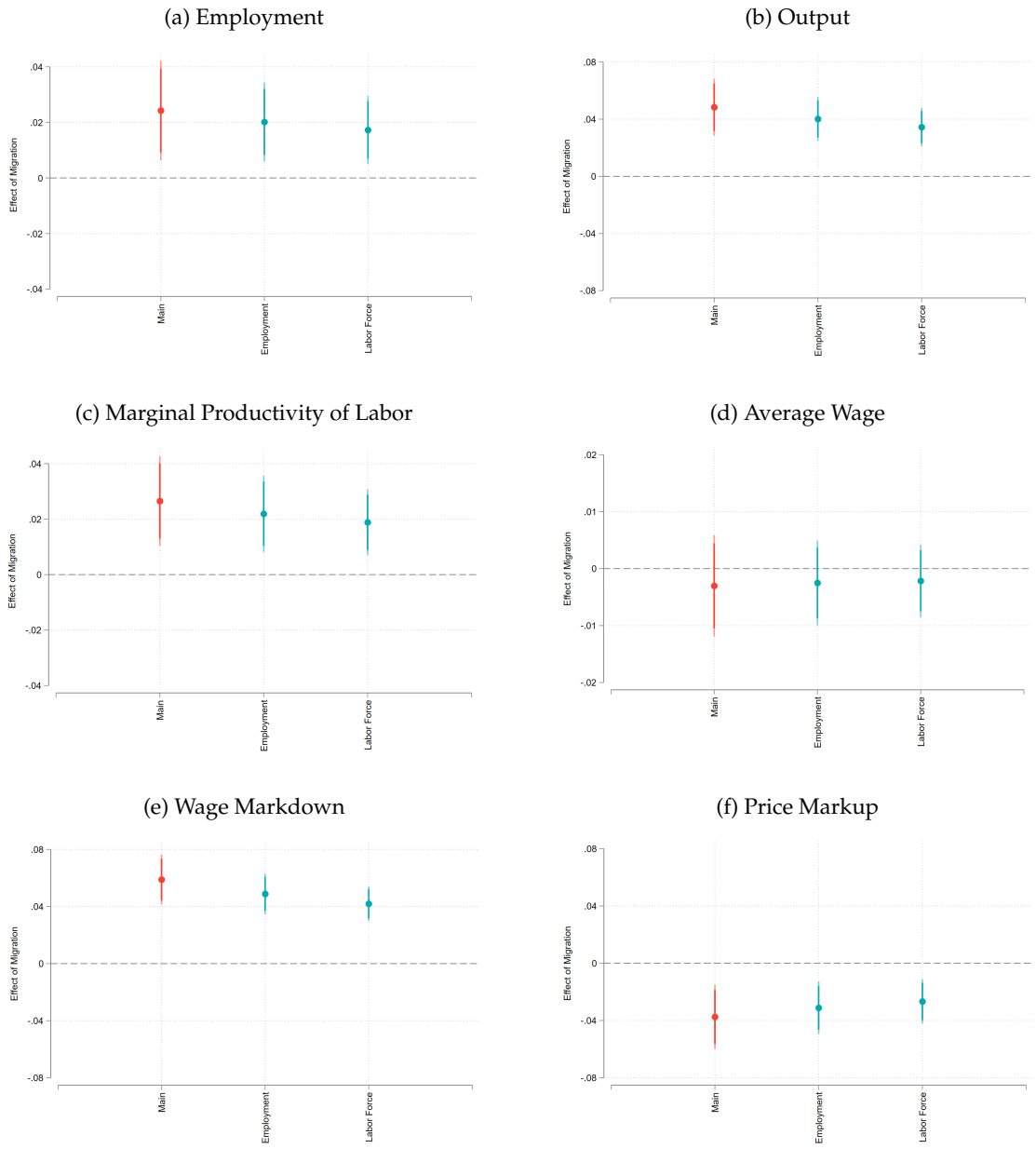
Figure B.4: Robustness exercise: Leave-one-out Top 5 Industries, 2012-2020



Notes. The coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. The red coefficient indicates the original estimated effect of the migration shock on each respective outcome. The blue estimates correspond to the same effect but omit the 2-digit industry specified on the x-axis. The estimates include Industry fixed effects at the 4-digit CIIU level. They also control for the Local Labor Market (LLM) variables specified in Section 5.2. The bars represent the 95% (light bars) and 90% (darker bars) confidence intervals. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

B.5 Alternative Independent Variable Definitions

Figure B.5: Robustness exercise: Alternative Definitions of Independent Variables, 2012-2020



Notes. The coefficients correspond to the estimation of the interaction between the main independent variable with a dummy variable that takes a value of 1 if the observation corresponds to a year between 2016 and 2020 by pooling all years in the sample following equation 6. The red coefficient indicates the original estimated effect of the migration shock on each respective outcome. The blue estimates represent the same effect, but calculated by changing the method to compute the share of migrants in each local labor market relative to the group specified on the x-axis. The estimates include Industry fixed effects at the 4-digit CIIU level. They also control for the Local Labor Market (LLM) variables specified in Section 5.2. The bars represent the 95% (light bars) and 90% (darker bars) confidence intervals. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

C Appendix: Market Power in the Colombian Manufacturing Sector

In this section, I will first show some descriptive evidence regarding the existence of market power of manufacturing firms in the Colombian labor market. In Table C.1, I show the average, median and standard deviation of the markdown and markup in Colombia for the different main economic activities that make up the manufacturing sector in the country.

Three main aspects are worth mentioning. First, for all the economic activities in the manufacturing sector considered, there seems to exist labor and/or product market power. Specifically, I estimate that, on average, the ratio between the marginal product of labor and the average wage paid by the firms in my sample is 1.82, indicating that for every additional dollar produced by the firm, the workers are only receiving 55 cents. For the case of the output market, there is also evidence of market power. My estimates suggest that consumers are being charged, on average, a price that is 41% higher than the marginal costs. Secondly, there is significant heterogeneity across economic activities within the manufacturing sector. Transportation, Paper, and Medical Equipment exhibit the largest markdown, whereas Clothing manufacturing, Oil refinery, and Other minerals exhibit the highest markups.

Table C.1: Markdown estimates by economic activity, 2013-2019

	Markdowns			Markups		
	Mean	Median	S.D.	Mean	Median	S.D.
Other Transportation	3.40	2.52	2.81	1.08	0.86	0.76
Paper	2.94	2.48	2.15	1.37	1.11	0.84
Medical Equipment	2.72	2.10	2.10	1.15	0.97	0.69
Basic Metal	2.57	2.04	1.84	1.28	1.09	0.83
Machinery and Equipment	2.39	1.84	1.90	1.19	0.99	0.80
Radio Equipment	2.32	1.44	2.07	1.27	1.11	0.72
Electric Equipment	2.31	1.84	1.78	1.30	1.13	0.65
Furniture/Other Industries	2.26	1.80	1.72	1.20	1.05	0.69
Printing	2.23	1.90	1.64	1.06	0.87	0.63
Wood	2.19	1.82	1.75	1.22	1.06	0.70
Oil Refinery	2.15	0.64	2.73	1.69	1.55	0.65
Other Minerals	2.06	1.26	2.19	1.63	1.19	1.20
Metal Manufacturing	1.98	1.49	1.66	1.23	1.05	0.73
Leather	1.88	1.51	1.37	1.35	1.20	0.63
Food and Beverages	1.86	1.64	1.16	1.45	1.23	0.81
Vehicles	1.69	1.27	1.30	1.29	1.13	0.63
Chemicals	1.44	1.11	1.20	1.57	1.33	0.88
Rubber/Plastic	1.42	1.18	0.98	1.39	1.21	0.71
Office Equipment	1.20	1.14	0.65	1.12	0.86	0.76
Textiles	1.20	1.01	0.93	1.53	1.36	0.75
Clothing manufacturing, tanning	0.96	0.76	0.79	1.79	1.58	0.90
Total	1.82	1.39	1.52	1.41	1.20	0.82

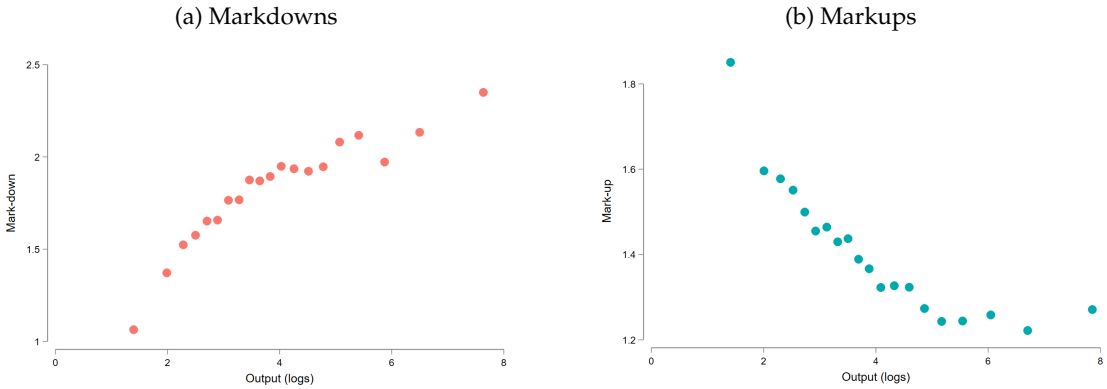
Notes. The Table shows the mean, median, and standard deviation of the markdowns in the Colombian manufacturing sector by economic activity. Source: Own estimates based on EAM data from DANE.

These values are in line with the labor economics literature estimating markdowns in different countries of the world. For instance, for the case of the US, Yeh et al. (2022) estimate and average markdown in the manufacturing sector of 1.53. In the case of developing countries, for instance, Estefan et al. (2024) estimate an average markdown of 1.49 for the manufacturing sector in Mexico. Finally, for the case of Colombia and by using an alternative methodology, Amodio and De Roux (2024) estimate a labor supply elasticity of 2.5, which implies a wage markdown of 1.4.

Regarding product markups, my estimates are consistent with markup estimations for the case of developed and developing countries. For instance, in the case of developing countries, Tortarolo and Zarate (2018) estimates a median markup for Colombia manufacturing firms equal to 1.78, De Loecker et al. (2016) find a median markup for the Indian economy of 1.34, and an average of 2.70.

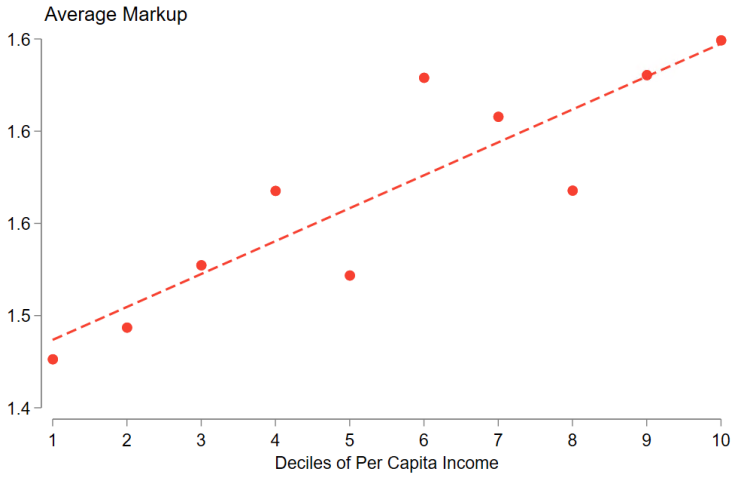
Furthermore, when analyzing the relationship between the labor market power of the firms and their size, Figure C.1 shows that the larger the firms are in terms of output, the lager the markdown they can impose. This result is consistent with other papers in the labor market power literature of developing countries (Estefan et al., 2024). Additionally, my estimates suggest that larger firms are also able to impose lower markups, on average.

Figure C.1: Firms' Market Power and Size



Notes. The figures show the relationship between sales (in logs) of firms and their wage markdown (Panel a) and product markup (Panel b). Source: Own elaboration based on EAM data from DANE.

Figure C.2: Relationship between Per Capita Income and Markup



Notes. The estimates include Industry fixed effects at the 4-digit CIIU level. They also control for the Local Labor Market (LLM) controls specified in Section 5.2. The bars represent the 95% (light bars) and 90% (darker bars) confidence intervals. Standard errors are clustered at the level of the local labor market level. Source: Own elaboration based on data from DANE.

D Technical Appendix

D.1 Construction of the Dataset

I follow standard data-cleaning procedures for the EAM dataset, as commonly practiced in the economic literature (see, e.g., Eslava et al., 2013; Fieler et al., 2018; Tortarolo and Zarate, 2018). First, I retain single-plant firms, and for multi-plant firms, I keep only the plant with the largest number of employees throughout the analysis period. I exclude firms classified as cooperatives, religious or solidarity organizations, third-sector organizations, or State-owned commercial and industrial companies, as well as those with any State capital ownership. Additionally, I drop firms with negative or zero values for capital, raw material consumption, intermediate consumption, production, total wage bill, or energy consumption. Firms with fewer than 10 employees in any year within the analysis period are also excluded. Finally, I remove firms with extreme outlier values for main variables (capital, employment, materials consumption, energy consumption, and production) where any values exceeds the median of the same variable by a factor of 8.

When estimating the wage markdowns and product price markups, I further exclude observations with markdowns or markups beyond the 1st or 99th percentiles.

D.2 Methodology for Price Indices Construction and Deflation Procedure

To construct plant-level price indices for materials and output, I followed the methodology of Eslava et al. (2013), utilizing a distinctive characteristic of the EAM: the provision of plant-level prices for each product produced and each material used in the production process, with a level of detail comparable to the 6-digit Harmonized System.

I calculated unit prices by dividing the total production value by the quantity for each product, then determined the average share of each product in the total output or materials over the analysis period. For each firm-product, I calculated the log change in price year-over-year, with extreme values truncated at the 1st and 99th percentiles. Missing values were imputed using product-industry-year, product-year, or industry-year averages, when available, in that order. I computed firm-level weighted averages of log price changes, using product shares as weights, and calculated within-year price deviations from the economy-wide average. The base-year price index was set to one plus the deviation from the industry average, with subsequent years calculated by adding the average log

price change. I normalized the indices to set the base year to 100, excluding outliers beyond the 1st and 99th percentiles.

Finally, I used the indices for output and materials to deflate firm-level outputs and inputs, DANE's capital price index for capital deflation, and the national CPI for wages.

E Production Function, Markdown, and Markup estimations

In this section, I go over the production function estimation methods used in this paper. Then, I will explain how the wage markdown, marginal productivity of production inputs, and profits were calculated.

E.1 Production Function Estimation

In this subsection, I will provide details on the estimation of firms' production function and the corresponding output elasticities. This section closely follows the details provided by Yeh et al. (2022). For the production function estimation, I will follow the proxy variable method proposed in the literature by Olley and Pakes (1996), Levinsohn and Petrin (2003), De Loecker and Warzynski (2012), and Ackerberg et al. (2015).

Consider the production function of the firm which is given by $Q_{it} = \Omega_{it} F(L_{it}, K_{it}, M_{it}, E_{it})$, where L_{it} represents labor, M_{it} are the intermediate materials used by the firm, K_{it} is capital, and E_{it} is the energy consumed by the firm. We have that Ω_{it} enters in a multiplicative way to the production function, which is observed by the firm before choosing their inputs but not by the econometrician. Then, taking into account measurement errors, we assume that the logged output of the firms is given by $y_{it} = ln(Q_{it}) + \omega_{it} + \varepsilon_{it}$, where ε_{it} represents the measurement error in the production function. This error term is not observed neither by the firm when they have to make production decisions nor the econometrician. Then, considering β as parameters in our production function, we have that the logged production function of the firm is given by:

$$y_{it} = f(l_{it}, k_{it}, m_{it}, e_{it}, \beta) + \omega_{it} + \varepsilon_{it}$$

This element ω_{it} is the main source of endogeneity when estimating production functions and output elasticities of production inputs. Following the "proxy method" we can consider materials

as our proxy variable which is going to be an invertible function of each period's productivity and the other inputs in the production function, therefore $m_{it} = m_{it}(\omega_{it}, l_{it}, k_{it}, e_{it})$. Therefore, there is a function h_{it} such that $\omega_{it} = h_t(m_{it}, k_{it}, l_{it}, e_{it})$.

Then, we have that

$$y_{it} = f(l_{it}, k_{it}, m_{it}, e_{it}) + h_t(m_{it}, k_{it}, l_{it}, e_{it}) + \varepsilon_{it}$$

Which implies that

$$y_{it} = \varphi_{it} + \varepsilon_{it}$$

Then, to estimate the production function parameters β we follow Ackerberg et al. (2015). We assume that m_{it} is our proxy variable or flexible input, whereas (l_{it}, k_{it}, e_{it}) are not fully flexible. With this at hand, we first estimate φ_{it} and ε_{it} non-parametrically by approximating y_{it} with a third degree polynomial with interaction terms. Then, once we estimate y_{it} we can estimate $\hat{\varphi}_{it}$ as the fitted values of that estimation, and $\hat{\varepsilon}_{it}$ as the corresponding residuals.

An additional assumption of the "proxy variable" method is the process under which we assume productivity evolves over time. We assume this is going to be a Markovian stochastic process, such that $E[\omega_{it}|\omega_{i,t-1}] = g_t(\omega_{i,t-1})$, such that $\omega_{it} = g_t(\omega_{i,t-1}) + \zeta_{it}$, where ζ_{it} is going to be the productivity innovation of period t, such that $E[\zeta_{it}|\omega_{i,t-1}] = 0$, which indicates that on average, the innovations to productivity today do not depend on the productivity in the previous period. Given this, we can approximate $\omega_{it}(\beta)$ in our data by:

$$\omega_{it}(\beta) = \hat{\varphi}_{it} - f(x_{it}; \beta)$$

Then, we can approximate $g_t(.)$ with a P^{th} order polynomial (in our case a third-order polynomial) such that

$$\omega_{it}(\beta) = \Omega_{it-1}(\beta)'\rho(\beta) + \zeta_{it}$$

$$\omega_{it}(\beta) = \sum_{p=0}^{P} \rho_p \omega_{it-1}^p + \zeta_{it}$$

Then, $\zeta_{it} = \omega_{it}(\beta) - \Omega_{it-1}(\beta)'\hat{\rho}(\beta)$. Where $\hat{\rho}(\beta)$ is just the set of coefficients we obtain from running a regression of $\Omega_{it-1}(\beta)$ on ω_{it}.

Finally, we know by assumption that capital is predetermined at each period, then we know that k_{it} should be not correlated with $\zeta_{it}(\beta)$, and we also know that the input decisions in period t should not be correlated with productivity innovations ζ_{it}. Therefore, we can use the set of lagged inputs and current capital as instruments for current input decisions in our production function (with their corresponding polynomials and interactions). Then, to obtain $\beta \in R^Z$ we estimate it through a traditional GMM estimation, by defining the following system of moment conditions

$$E(\zeta_{it}(\beta) z_{it}) = 0$$

Therefore, our estimated coefficients are going to be given by

$$\hat{\beta} = \text{argmin}_{\beta \in R^Z} \sum_{m=1}^{Z} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \zeta_{it}(\beta) z_{it}^m \right)^2$$