# Immigration and Occupational Downgrading in Colombia

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January 2024

## Abstract

Between 2015-2019, approximately 1.8 million Venezuelans fled an economic and political crisis into neighboring Colombia. Despite being well-educated on average, these migrants disproportionately entered occupations that typically employ less-educated Colombians. I use a model of labor demand with imperfect substitutability between migrants and natives to study the effect of migrant occupational downgrading on native wages and inequality. Counterfactual scenarios reveal that migrant downgrading amplifies the negative wage effect of migration for natives without completed secondary schooling by 30%, and this increases to 80% after allowing for full capital adjustment in the long term. At the same time, migrant downgrading has little consequence for the wages of more-educated natives, who benefit from reduced competition but are harmed by reductions in aggregate productivity. The results highlight the consequences of migrant downgrading for wage inequality and productivity. In developing countries, these consequences are amplified by low imperfect substitutability across education groups.

**Keywords:** immigration, occupational downgrading, wage inequality
**JEL Codes:** F22, J24, J61

# 1 Introduction

It is well-documented that migrants across the world are often over-educated in their occupation relative to natives (Piracha *et al.* , 2012; Chiswick & Miller, 2009; Leuven & Oosterbeek, 2011; Eckstein & Weiss, 2004; Friedberg, 2000). This is particularly true in forced displacement contexts, where migration is typically sudden, driven by push factors in the home country, and where migrants are less likely to have a plan for employment relative to purely economic migrants (Brell *et al.* , 2020). While the consequences of this downgrading for migrant earnings and assimilation are well-documented, it is less well-understood how this downgrading may affect economic outcomes for natives in the host country (Fasani *et al.* , 2022). First, migrant occupational downgrading could increase inequality by concentrating economic competition among poorer natives. Second, it could hinder increases in total economic output and aggregate wages - a potential benefit of migration - if migrants are concentrated in occupations where they are less productive. This is particularly worrying given the increasing global number of forcibly displaced persons, which more than doubled from 41 million to 89 million between 2010-2021 (UNHCR, 2021). Over 80% of those forcibly displaced across borders are hosted in a developing country, where increased wage inequality and lost opportunities for economic growth are all the more costly.

The primary contribution of this paper is to develop a framework to estimate the consequences of migrant downgrading for native wages across the education distribution. Following a framework that has been applied in the literature to study the wage effects of migration, I estimate a nested-CES model of labor demand that incorporates imperfect substitutability between migrants and natives and imperfect substitutability across education groups (Ottaviano & Peri, 2012; Manacorda *et al.* , 2012; Card, 2009; Borjas & Katz, 2007; Borjas, 2003). Migrants and natives generally work different jobs, complete different tasks, and have different skills, and the extent to which they are substitutes or complements is an empirical question that will vary across contexts and occupations. In the papers just cited, migrants are assumed to compete with natives within their education group. However, if occupational downgrading leads migrants to compete with less-educated natives, this becomes a misclassification problem that may bias the estimated substitutability parameters (Dustmann *et al.* , 2016, 2013). I thus incorporate occupational downgrading into the estimation, allowing me to directly quantify the effect of migrant downgrading on native wages.

The second contribution of this paper is to apply this framework in a developing country setting. Between 2015-2019, approximately 1.8 million migrants fled Venezuela's economic and political crisis into neighboring Colombia, increasing the Colombian population by al-

most 4%. Despite being similarly educated as Colombian natives, and despite sharing a common language and similar cultural background, these Venezuelan migrants are highly concentrated in occupations that typically employ less-educated workers: over 25% of working Venezuelan migrants in Colombia in 2019 had post-secondary education, and around 75% of them were in occupations where the modal native did not go to college, relative to around 30% for college-educated natives. The five most common occupations for migrants with post-secondary education are, in order, restaurant work, street vending, working in a barbershop or beauty salon, shop owner, and domestic service. This situation has stimulated debate over the consequences of migrant downgrading for the Colombian economy.[1] Furthermore, Venezuelan downgrading has been proposed as an explanation for the observed effects of Venezuelan migration on wage inequality in Colombia and Latin America (Olivieri *et al.* , 2021b; Lombardo *et al.* , 2021). By specifying a model of labor demand that incorporates occupation downgrading, I am able to test this directly.

A strong advantage of this setting is that Venezuelan out-migration was driven by a drastic increase in poverty, violence, and inadequate quality of life, stimulated by the sudden collapse of oil prices in 2014, and unrelated to changes happening in Colombia over this period (Migration Policy Institute, 2020). Thus, the endogeneity of migration timing is less of a concern relative to a setting in which migrants are attracted by economic pull-factors. There was no change in migration to Colombia from any other country over this period. There is also broad geographic dispersion of migrants across Colombia, alongside high-quality household survey data on labor market outcomes for both migrants and natives, resulting in a sample of over 1.5 million natives and 30,000 migrants over the study period. Therefore, this presents a unique opportunity to study the economic effects of a massive and supply-driven migration wave.

Using geographic variation in migrant arrival across 79 metropolitan areas, I estimate a CES model of labor demand that is nested by education level and migration status. Following the literature, I estimate the elasticity of substitution between migrants and natives using variation in the migrant-native ratios of wages and labor supplies across metro areas and years (Ottaviano & Peri, 2012; Manacorda *et al.* , 2012; Card, 2009). Intuitively, a low sensitivity of the migrant-native wage ratio to an increase in migrant labor supply within an education group implies a high migrant-native substitutability. This requires the

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[1]For example, the think-tank Global Americans stated "the Colombian economy can benefit from the vast talent pool of Venezuelan professionals who have migrated to Colombia and currently rely on informal work when they could be more productive in other sectors" (Guzmán & Marmolejo, 2021). A Brookings report stated "If properly integrated into the labor force, [Venezuelan migrants] represent a largely productive cohort which could contribute to economic growth and productivity gains" (Bahar *et al.* , 2018).

identification assumption that migrant locational sorting into metro areas is uncorrelated with the potential *migrant-native wage ratio*, distinct from the traditional assumption that locational sorting is uncorrelated with potential wages. To account for the possibility that this assumption is violated, I use an instrumental variable strategy based on the historical settlement patterns of Venezuelans (Altonji & Card, 1991; Card, 2001), and the similarity of OLS and 2SLS coefficients indicates that there is little migrant locational sorting according to this wage ratio. I also use internal migration data to confirm that results are not biased by native spatial arbitrage (Borjas, 2003; Borjas & Katz, 2007; Monras, 2020).

As discussed, in the traditional education-nested labor demand function, one estimates the degree of imperfect substitutability between migrants and natives within an education group. To study migrant downgrading explicitly, one needs to somehow incorporate occupations into this labor demand function. One approach is to add occupation nests in the production function to estimate migrant-native substitutability within education-occupation groups. However, this requires cutting the metro area-specific migrant sample along another dimension, which is not feasible given the migrant sample size. Furthermore, unlike education, occupation is not fixed and natives may endogenously sort across occupations in response to migration (Foged & Peri, 2016; Peri & Sparber, 2009). Therefore, I take a different approach - I keep the demand function nested at the education level, and I use information on migrants' observed occupations to "downgrade" them to education groups according to the typical education required for their observed occupation in Colombia.[2] Specifically, I iteratively randomly assign migrants to education groups with probability weights equal to the pre-2015 native education composition of their occupation. I thus estimate the substitutability between natives in an education group and the migrants they compete with. The advantage of this approach is that it is a relatively simple framework for estimating the wage effects of migrant downgrading by education group without having to explicitly incorporate occupations into the production function. This is explained further in section 4.[3]

I estimate migrant-native elasticities of substitution of around 7 for workers with post-secondary education, implying levels of short-run substitutability comparable with that of high-skill migrants recently arrived in the UK (Manacorda *et al.*, 2012). This increases to

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[2]Unfortunately, I do not observe the occupation worked in Venezuela. Under this approach, downgrading is defined according to the mismatch between the migrants' education and observed occupation in Colombia.

[3]An interesting question is whether migrants who downgrade carry skills and experiences into low-skill occupations that increase their productivity. This would increase their effective labor supply and amplify their effect on wages in these occupations. To evaluate this, I estimate wage regressions to identify the education premia for migrants in low-skill occupations, and I find small wage benefits associated with schooling for migrants who downgrade. I use these coefficients to adjust the effective labor supplied by migrants in low-skill occupations, and this has little effect on the estimated parameters in practice.

15 for workers without completed secondary – large considering that most Venezuelans have been in Colombia for only a few years, and it is comparable in magnitude with the long-run migrant-native substitutability estimated in the U.S. (Ottaviano & Peri, 2012).

Using the estimated parameters, I calculate that migration over the 2014-2019 study period decreased wages by 4.1%, 3.4%, and 0.3% respectively for natives without completed secondary, with completed secondary, and with post-secondary education. This holds capital fixed, such that there are diminishing returns in the labor aggregate. However, I demonstrate that these distributional effects persist when I allow capital to adjust in the long-term (Ottaviano & Peri, 2012). The magnitudes of these short-term wage effects are broadly consistent with existing estimates of the effects of Venezuelan migration in Colombia over this period (Lebow, 2022; Delgado-Prieto, 2022; Penaloza-Pacheco, 2022; Santamaria, 2020; Bonilla-Mejía et al. , 2020; Caruso et al. , 2019).[4] These papers are "non-structural" in that they make no assumptions about the structure of labor demand, and they are informative about the total effects of migration on native wages (Dustmann et al. , 2016). Thus, it is reassuring that my estimates are consistent with these non-structural results. Also consistent with existing evidence, I calculate that migration affects wages of existing migrants much more negatively than native wages, driven by high imperfect substitutability between migrants and natives (Bonilla-Mejía et al. , 2020).

Finally, I simulate a counterfactual in which I calculate total wage effects after migrants are reallocated to compete with natives in their observed education group. This represents a scenario in which there is no migrant downgrading relative to similarly educated natives.[5] This reallocation reduces the wage effect for natives without completed secondary schooling from -4.1% to -3.1%. At the same time, despite facing increased within-group competition, wages of natives with completed secondary are unchanged, and the wage effect for natives with post-secondary falls only slightly from -.2% to -.6%. The effect of migration on inequality, measured as the wage ratio of natives with post-secondary to natives without completed secondary, reduces by 36%. Under long-term capital adjustment, the aggregate wage effect of migration is zero, but the distributional consequences of migrant downgrading persist.

Why does the large increase in competition for educated Colombians not translate into similarly large wage losses? One channel is that, because migrants and natives are less

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[4]While these papers are consistent in finding negative wage effects concentrated on less-educated Colombians, there is discrepancy in their magnitudes, and the reasons are explored extensively in Lebow (2022). Papers find similar effects of Venezuelan migration for less-educated natives in Ecuador and Brazil, while evidence in Peru is mixed (Groeger et al. , 2022; Olivieri et al. , 2021a; Zago, 2020; Morales & Pierola, 2020).

[5]This counterfactual takes the migrant inflow as given. In the absence of barriers to occupational choice, more high-skill Venezuelans may choose to migrate. I do not consider this general equilibrium effect here.

substitutable in high-skill occupations, the marginal effect of migration on native wages is lower in these occupations. However, in counterfactual simulations, I find that this effect is relatively small relative to the total wage effect. More important are the large increases in total output that result from moving migrants into more productive and relatively under-supplied jobs, and this increases everyone's marginal product and counteracts the greater competition faced by more-educated natives. I also find that the low substitutability across education groups, a common characteristic of developing countries, severely amplifies the consequences of downgrading for less-educated natives, by segmenting the economy such that wage effects remain concentrated within education groups. When I set the across-education group substitutability parameters to the levels observed in the U.S., the consequences of migrant downgrading for natives without completed secondary reduce by around 80%.

This counterfactual assumes that the quality of education in Venezuela and Colombia is comparable. In section A2, I evaluate this assumption, first by comparing cross-country rankings in education quality, and second by estimating the education earnings premia for Colombian and Venezuelan migrants in the U.S. I find that, if anything, Venezuelan education is slightly higher quality and generates higher wage returns than Colombian education (and this is unlikely to be driven by different migrant selection to the U.S.), in which case the model underestimates the true distributional consequences of downgrading.

In treating native labor supply as fixed, I assume that effects occur along the wage and not the employment margin. In many previously studied settings, this assumption would be problematic (Borjas & Edo, 2021). However, there is now extensive evidence that the labor market effects of Venezuelans in Colombia have been mostly on the wage margin, consistent with natives having low reservation wages. There is evidence of decreases in employment among some subgroups, notably workers under age 25, formal sector workers, and women, though the magnitude and significance of these effects are highly sensitive to empirical specification (Lebow, 2022; Delgado-Prieto, 2022; Pedrazzi & Penaloza-Pacheco, 2022; Otero-Cortés et al. , 2022).[6] I drop these subgroups as a robustness check that compositional employment changes do not bias the results.

The results highlight the importance of policies to reduce occupational downgrading among the forcibly displaced, not only to directly benefit migrant workers but also to mitigate negative wage effects for the most vulnerable natives and to maximize the economic gains from migration. Linguistic barriers are often a focus in the discussion of refugee integration, yet downgrading has occurred in this setting despite both migrants and natives speaking

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[6]Lebow (2022) finds that a 1pp increase in the migrant share decreases employment for young workers by .5pp and formal salaried employment by less than .1pp.

Spanish (Arendt *et al.* , 2020; Lochmann *et al.* , 2019). Instead, other well-recognized barriers have effectively closed off access to high-skill occupations for many migrants, including inadequate systems for education recognition and occupational licensing, gaps in access to legal status, lack of employer networks, and discrimination (Bahar *et al.* , 2022; Graham *et al.* , 2020; Chaves-González *et al.* , 2021; World Bank, 2018; Bahar *et al.* , 2018). These have been documented extensively as causes of migrant downgrading in Colombia, but much more work is needed to understand to what extent and for which occupations each of these barriers applies. It may also be that high-skill occupations require more country-specific experience or soft skills (for example, legal work) or have lower short-term elasticities of demand (for example, professional and financial services may have existing clients and fee structures and thus take time to expand in response to increasing labor supply). Thus, in addition to addressing remaining gaps in legal status, fast-tracking educational recognition and occupational licensing, and facilitating migrant-employer networks, promising policy avenues include training migrants to adapt country-specific soft skills and knowledge, or helping to increase elasticity of demand among firms where there is potential to hire migrants. We crucially need additional research on these channels to inform migration labor market policy.

A vast literature studies the causal effects of sudden migration or forced displacement on native employment and earnings.[7] A recent review by Verme & Schuettler (2021) finds that negative effects on native economic outcomes are most likely to be observed in middle-income developing countries and to be most pronounced for less-educated natives working in the informal sector.[8] However, developing countries have received less attention in the literature on the economic effects of migration and forced displacement, even though the majority of forced displacement occurs in developing countries. This paper highlights migrant downgrading as a driver of the economic consequences of migration for low-wage workers in developing countries, in particular where low substitutability across education groups shields more educated natives from increasing competition in low-skill occupations.

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[7]For example, see Edo (2020); Peri *et al.* (2020); Clemens & Hunt (2019); Peri & Yasenov (2019); Clemens *et al.* (2018); Borjas & Monras (2017); Foged & Peri (2016); Friedberg (2001); Hunt (1992); Card (1990).

[8]An important example is Syrian refugee migration to Turkey, which also disproportionately affected the informal sector, and there is evidence for negative employment effects and potentially small negative wage effects among less-educated and informal workers (Altındağ *et al.* , 2020; Aksu *et al.* , 2018; Ceritoglu *et al.* , 2017; Tumen, 2016; Del Carpio & Wagner, 2015).

# 2    Background: The Venezuelan "Exodus"

Venezuela and Colombia were once part of the 19th-century "Gran Colombia" state that encompassed much of northern South America. They have historically had close relations characterized by a common culture and language, trade exchanges, and migratory flows. Until recently, favorable economic conditions meant there was relatively little migration out of Venezuela. Instead, Venezuela was a major recipient of Latin American migrants, who were attracted by relatively low poverty rates and generous social programs, including Colombians fleeing the decades-long civil war in Colombia.

This began to change when Hugo Chávez begin his term as President in 1999. Migration to Venezuela slowed and members of the Venezuelan upper class began to migrate away with concerns that socialist reforms were paving the way for economic instability. These migrants went primarily to the US and Spain and were small in number relative to the current migration out of Venezuela (Freitez, 2011). Shortly after the death of Chávez in 2013 and the inauguration of his successor Nicolás Maduro in 2014, global oil prices collapsed. This, combined with a dramatically diminished private sector and weakened oil and agricultural industries, prompted a sudden and severe economic recession. By 2016, Venezuela entered hyperinflation. By 2018, according to studies from various sources including universities in Caracas, GDP had contracted by almost 50%, the poverty rate increased to around 90%, and around one-third of the population reported being forced to skip meals (Reuters, 2018). Access to water, electricity, and essential healthcare services and medicines became increasingly scarce, and the murder rate rose to one of the highest in the world (Wilson Center, 2019; Reina *et al.* , 2018). The Maduro administration showed little capacity to address the crisis and used violence and intimidation to weaken the growing political opposition. Prospects for political or economic change were slim, especially after the overwhelming defeat of the opposition party in regional elections in 2017.

Between 2015 and 2019, 4.8 million migrants fled Venezuela, making Venezuela the second-largest country of origin for internationally displaced people after Syria. Colombia, the neighbor closest to the population centers of Venezuela, received an estimated 1.8 million of these migrants over this period, more than any other country, and representing almost 4% of the Colombian population (Migration Policy Institute, 2020). This is the first time Colombia has received a large migration wave from another country: according to the 1993 census, .13% of the population was Venezuelan born and .2% was born in a different foreign country. Figure 1 shows that these rates remained relatively constant until the onset of the Venezuelan migration in 2015. The arrival rate increased in 2016 and again in 2017, with

Figure 1: Foreign-Born Population in Colombia
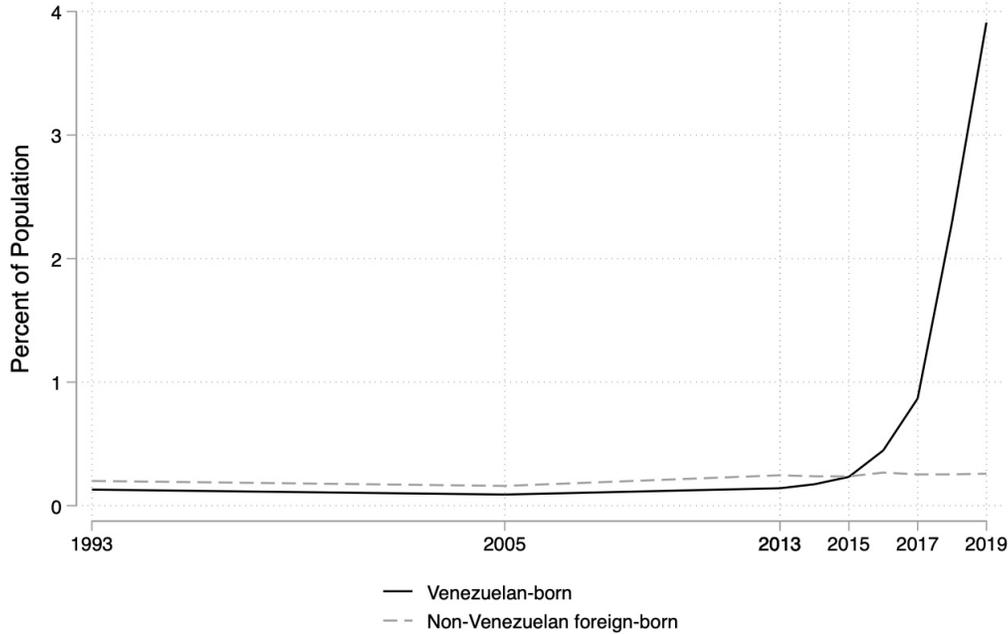


Source: GEIH (2013-2019), Population Census (1993, 2005)

the majority of migrants arriving between 2018-2019. This migration was sudden, drastic, and entirely unprecedented.

There were relatively few requirements for migrants to cross the border, and those without legal documents could pass around border control checkpoints on paths commonly known as "trochas" (World Bank, 2018). Within Colombia, there were no restrictions on where migrants were allowed to live. The majority moved to urban areas and there were few camps. Figure 2 shows the migrant share of the population across 79 metro areas in 2019, where a migrant is defined as someone who was living in Venezuela 5 years ago. There is extensive variation in migration across Colombia. Migrant shares tend to be larger closer to the Venezuelan border, in many cases exceeding 10% of the metro area population. In Cúcuta and Riohacha, two cities close to the primary entry points along the border, migrant shares are around 16% and 11% respectively. In Bogotá, Medellín, and Cali, the three largest cities in Colombia, migrant shares range from 4-5%. For other cities, they are below 1%.

The Colombian government created a temporary resident VISA beginning in January 2017 (the Permiso Temporal de Permanencia, or PEP) that provided documented migrants a two-year work permit and access to education, health, and financial services. Since then, the government has implemented various additional rounds of regularization and renewed the PEP for those who first received it. Most notably, in 2018 the government offered regulariza-

Figure 2: Venezuelan Migrants in Colombia (2019)
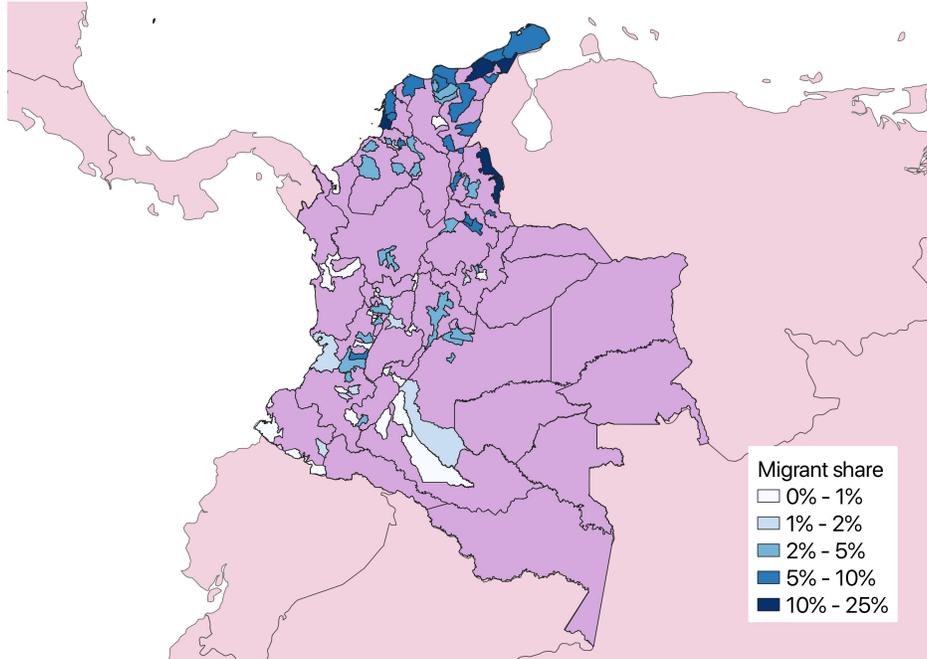


Source: GEIH (2019)

tion and work permits to 442,462 migrants who had until then been undocumented, either because they entered illegally or overstayed their temporary permit. These migrants could now benefit from social services, safety nets, and the right to work, making this arguably one of the most generous migrant regularization programs in recent history (Bahar *et al.* , 2021). Subsequent research has shown large benefits of this program for migrant well-being and use of public services (Ibanez *et al.* , 2022). However, this regularization covered only a subset of Venezuelans in the country, and by 2019 only around 40% of migrants in Colombia were estimated to be documented under the various existing regularization programs (Migración Colombia, 2019). Furthermore, in 2019 around 90% of migrant workers remained in the informal sector relative to around 50% of natives (defined according to enrollment in mandatory health and pension programs). This is despite a large wage premium for migrants in the formal sector, highlighting the barriers that prevent migrants from formalizing even after receiving legal status (Ibanez *et al.* , 2022).

# 3    Data and Migrant Characteristics

Data for this project come primarily from the Colombian National Integrated Household Survey (GEIH), which is a nationally-representative survey collected by the National

Department of Statistics (DANE) and is the official source for labor market indicators in Colombia. Since 2013, this survey has included a migration module that records where a person was living 1 and 5 years ago and can therefore be used to measure both migration rates and labor market outcomes for natives and migrants across locations and over time. This is rare in the developing country setting and necessary to estimate the model.[9]

Colombia is divided into a capital district and 32 departments, which are further divided into 1,122 municipalities. I group municipalities into metropolitan areas according to commuting patterns. The goal is to generate a geographic unit that represents a contiguous labor market in which workers compete. I follow Duranton (2015) and use a recursive algorithm based on a 10% commuting threshold: a municipality is grouped with another municipality if over 10% of its residents commute to work in that municipality. They are then treated as a single unit in the next round of the algorithm, and this is repeated until no more municipalities meet this threshold. This is done using data from the 2005 census, which is the latest year before the start of the migration period in which this commuting data are available. The algorithm results in 184 metro areas with at least 30,000 residents in 2005, and these units are relatively independent of the choice of commuting threshold.[10]

The GEIH does not survey people in all of these metro areas and in others has a small sample. I therefore restrict my analysis to the 79 metro areas that contain at least 300 observations per year over the study period, representing around 80% of the Colombian population and 90% of Venezuelan migrants. The GEIH is designed to be representative of a smaller group of 23 metro areas that are loosely overlapping with my largest 23 metro areas, but not for areas finer than this. Thus, as a robustness check, I conduct analysis using the 23 metro areas for which the GEIH is officially representative and the results do not qualitatively change. I also use an instrumental variable based on the complete 2005 census, which will help to reduce the effect of measurement error in migration rates.

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[9] While the GEIH is not intended to be representative of Venezuelan migrants in Colombia, it is increasingly being used to track the Venezuelan population across Colombia over time (Graham *et al.* , 2020). The sample size is large enough to include a substantial number of migrants, with over 30,000 migrants in my estimation sample. Another data source is the official migration estimates imputed by the Colombian Migration Unit, but these likely undercount unregistered migrants (Tribín-Uribe *et al.* , 2020). A final option is the 2018 census, which only measures a snapshot in January-September 2018, and these estimates of the migrant share are closely correlated with those of the 2018 GEIH ($\rho = .76$ across metro areas in my sample).

[10] While in some cases they are identical to the officially defined metropolitan census areas (for example, in the case of Medellín), in others they are distinct (for example, the constructed areas of Bogotá, Calí, and Baranquilla all include substantially more municipalities than the official census areas). The official census metro areas are politically determined in consideration of factors such as allocation of city resources and jurisdiction of city government activity and thus are not always the most appropriate unit of economic analysis. See Duranton (2015) for a detailed discussion.

I define a migrant as anyone who was living in Venezuela 5 years ago.[11] In Table A1, I display the characteristics of working-age migrants and natives in my sample. In 2019, migrants and natives had a similar gender composition and migrants were younger, with an average age of 32.1 compared to 39.4 for natives. The migrant profile became slightly younger and more female over this 2014-2019 period, and these demographic characteristics are controlled for in the analysis. As I discuss later on, in Section A4 I estimate a version of the model that includes nests for gender and age, but this does not meaningfully affect the results by education group, which are the main emphasis of this paper. In 2019, migrants were more likely to have completed secondary education but less likely to have post-secondary. Still, 24.5% of migrants, relative to 27.7% of natives, have some post-secondary, indicating that this is not a low-skill migration wave. Migrants who arrived later were slightly more educated, but the last row of Table A1 shows that they continued to enter occupations that require similarly low levels of education. Thus, the changing rate of migration by occupation skill group over the sample period, which drives estimation in my analysis, is driven mostly by changes in the total number of migrants arriving in each metro area and not by the changing occupation composition of migrants. The approximately 82% labor force participation rate and 15% unemployment rate for migrants remained relatively constant during this period. Finally, despite having similar levels of completed education, migrant hourly wages were 45% lower than native wages. While native wages in the sample increased steadily by 4% over this period, migrant wages decreased by 27%. This suggests that imperfect substitutability between migrants and natives causes migrant wages to decrease disproportionately in response to an increase in migrant labor supply.

One way to characterize the severity of migrant downgrading in Colombia is to calculate the share of migrants who have a level of education greater than the mode in their occupation, which is a common method in the literature (Leuven & Oosterbeek, 2011). This results in an estimate of 52% of migrants, relative to 34% of natives, who are over-educated. Compare this with estimates of immigrant over-education calculated using the same method in other countries, which range from 16% in Denmark to 24% in the UK, 28% in the US, and 39% in Spain (Piracha et al. , 2012; Sanroma et al. , 2008). This number will generally be larger for recently arrived migrants - for example, it is 52% among male migrants in New Zealand

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[11]Because so few migrants were in Colombia before 2014, this measure is approximately the stock of migrants who arrived since 2014. This measure also includes Colombian-born return migrants, who make up around 20% of all migrants from Venezuela during this period. Many of these migrants went to Venezuela during Colombia's civil war, some as early as in the 1970s, and have lived in Venezuela for decades. These migrants also affect the local labor supply and are often in similar locations as Venezuelan born-migrants, so excluding them could cause an overestimation of the labor market effects of migration. Ideally, one could study the effects of each group separately, but they are empirically difficult to untangle due to the close correlation in the location of foreign-born and return migrants. See Lebow (2022) for a detailed discussion.

Table 1: Occupational Downgrading by Education

| Observed education: | Natives | | | Migrants | | |
|---|---|---|---|---|---|---|
| | < Secondary | Secondary | Post-Secondary | < Secondary | Secondary | Post-Secondary |
| **Assigment to education distribution in occupation:** | | | | | | |
| < Secondary | 60.7% | 46.7% | 19.4% | 59.6% | 53.5% | 43.3% |
| Secondary | 26.9% | 31.3% | 19.9% | 27.8% | 30.2% | 27.8% |
| Post-Secondary | 12.4% | 22.0% | 60.7% | 12.6% | 16.3% | 29.0% |
| N | 84,170 | 84,681 | 76,429 | 4,904 | 5,355 | 3,713 |
| (Row %) | ( 34.3%) | ( 34.5%) | ( 31.2%) | ( 35.1%) | ( 38.3%) | ( 26.6%) |

Sample restricted to workers age 15-64 in 2019, residing in one of 79 primary metro areas, and with completed education. A migrant is defined as anyone who was living in Venezuela 5 years before the survey. In each row, workers are re-assigned to education groups using the education distribution in their occupation (of natives between 2010-2014). Source: GEIH.

who arrived within five years (Poot & Stillman, 2010). Therefore, migrant over-education in Colombia is large but within the range of estimates observed in other countries.

A downside of this approach is that it relies on the modal education group, rather than the full distribution of education groups, within an occupation. Therefore, in this paper, I use an alternative method to measure migrant downgrading: I re-assign migrants to education groups based on the education distribution of natives in their observed occupation in Colombia between 2010-2014 (before the mass migration began). For example, 14% of migrants are in the "restaurant workers" occupation, which includes waiters, bartenders, and chefs. Among natives in this occupation between 2010-2014, 61% did not complete secondary, 27% completed secondary, and 12% have post-secondary. By assigning migrant restaurant workers to education groups using these proportions (.61, .27, and .12 of each unit of labor is assigned to each group respectively), I can observe the extent to which migrants are concentrated in occupations that typically employ each education group. This is the assignment mechanism that I will use in my estimation, which I explain further in Section 4.[12] In Table 1, I implement this for both migrants and natives in 2019. Among migrants with post-secondary, only 29% of those working in their occupation typically have post-secondary. For natives with post-secondary, this rate is 61%, demonstrating the striking level of downgrading among well-educated migrants.

A final way to characterize the degree of migrant downgrading, which is useful for expositional purposes, is to plot the concentration of migrants and natives across all of the 82 ISCO-68 occupations recorded in the GEIH. This is plotted in Figure 3. On the horizontal

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[12]This downgrading concept, like those based on modal education, uses the native occupation-education distribution as a benchmark according to which downgrading is defined. Alternatively, downgrading could be defined according to objective skill requirements. Absent a convincing way to classify the GEIH's ISCO-68 occupation groups by skill requirements, I do not take this approach.

axis, the occupations are ranked by the mean native education in that occupation between 2010-2014. It is clear that migrants have disproportionately entered lower-skill occupations. The top five occupations for migrants are labeled on the graph, and they are, in order, street vendors, restaurant workers, construction workers, domestic servants, and barbers or beauty salon workers. A natural question is whether this downgrading persists after controlling for observable characteristics. In Figure 4, the black markers plot the relative concentration of migrants in each occupation, or the ratio of the share of migrants over the share of natives. The size of each dot is proportional to the total number of migrants. This ratio is mostly above one for lower-skill occupations and below one for higher-skill occupations, demonstrating that migrants tend to be more concentrated relative to natives in low-skill occupations. The red triangles plot these relative concentrations when migrants are instead reassigned to the same occupation composition of natives within their 5-year age bin, education group, gender, metro area, and year. These relative concentrations are clustered much closer to the line at $y = 1$, though they remain below this line at high-skill occupations due to migrants' slightly lower post-secondary attainment. The results imply that, if migrants worked the same jobs as natives with similar characteristics, they would be substantially less concentrated in low-skill occupations.

In my analysis, I define downgrading according to the mismatch between migrants' completed education and the education typically worked by natives in their occupation. This makes the key assumption that schooling quality is comparable in Colombia and Venezuela. In Section A2, I compare the quality of the Colombian and Venezuelan education systems in two ways. First, I look at the 2009 Programme for International Student Assessment, which evaluates 15-year-olds' knowledge in reading, math, and scientific literacy. Out of 74 countries, Colombia and Venezuela ranked extremely close in every category, though Venezuela ranked slightly higher in all categories. Second, I conduct an analysis of the education earnings premium for Venezuelan and Colombian migrants who were educated at home and subsequently migrated to the U.S. Using the 2015 American Community Survey, I find that, controlling for observable characteristics, the earnings premia for secondary and post-secondary education are similar for migrants from each country, and the post-secondary earnings premium is if anything higher for Venezuelans. This is especially true for younger migrants who migrated after 1990, which is the group most comparable with the migrant population in Colombia. I also evaluate whether this difference in education earnings premia could be driven by differences in migrant selection patterns by comparing the share of the home-country population within each education group that migrated to the U.S., and I find that educated Venezuelans are unlikely to have a stronger selection on latent ability. Overall, the evidence indicates that the quality of secondary and post-secondary education

13

Figure 3: Concentration of Migrants and Natives Across Occupations
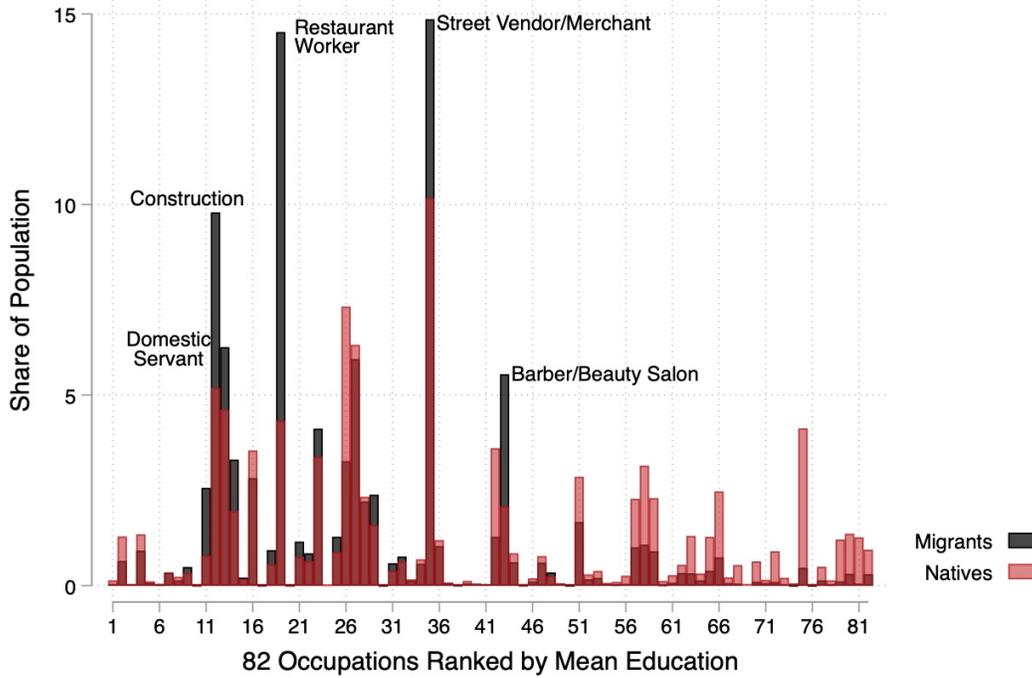


Figure 4: Relative Concentrations Observed and Predicted by Observables
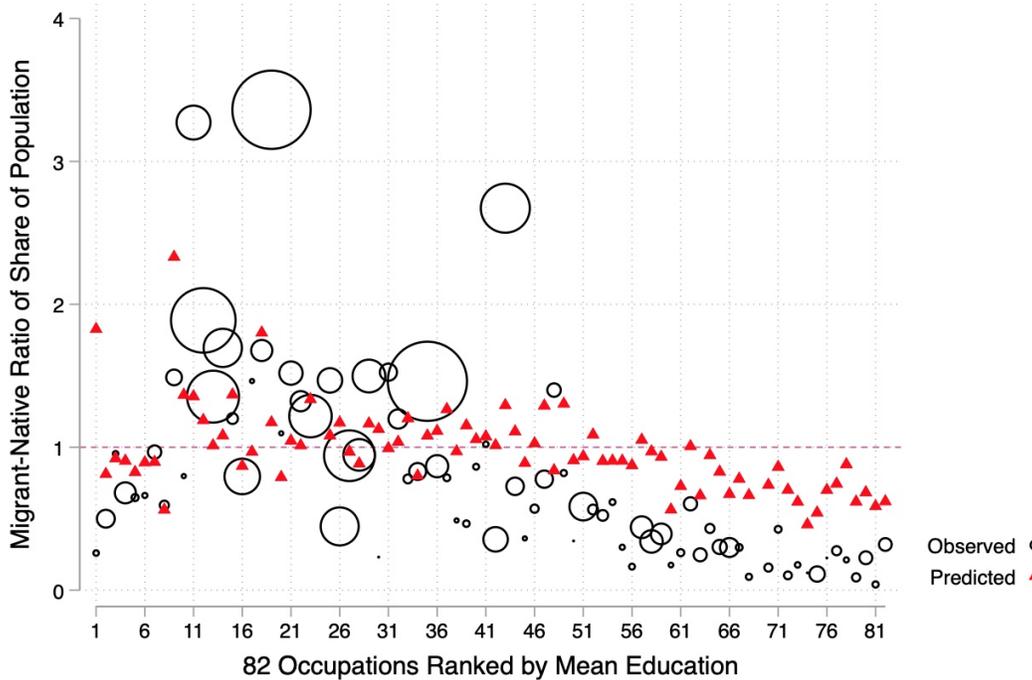


Source: GEIH 2019. Sample includes urban workers age 15-64. Black markers measure the share of migrants over the share of natives in each occupation. The circle size is proportional to the size of the migrant population. Red triangles plot the predicted values if migrants were in the same distribution of occupations as natives within the same age group, education group, gender, metro area and year.

14

is likely similar across countries and if anything higher in Venezuela, which would lead me to underestimate the true scale of migrant occupational downgrading.

# 4 Model and Estimation

## 4.1 Nested CES Framework

I consider a model of CES labor demand disaggregated by three education groups and nativity status. Even with only six cells, a fully flexible production function would require estimating 30 cross-group elasticities. To reduce the number of parameters estimated, I use a nested CES structure, following an extensive literature in labor economics that has used this framework to study relative changes in labor supply and wage inequality (Katz & Murphy, 1992; Card & Lemieux, 2001). Following Ottaviano & Peri (2012) and Manacorda *et al.* (2012), I allow for imperfect substitutability between migrants and natives, which was shown to be relevant for estimates of the wage effects of migration, and I extend these models by incorporating occupational downgrading into the migrant education assignment mechanism.

Firms produce output, $Y$, according to a constant-returns-to-scale Cobb-Douglas production function:

$$Y = AK^{1-\zeta}L^{\zeta} \tag{1}$$

where $K$ is capital, $\zeta$ is the labor share of income, and $A$ is a skill-neutral technology parameter. Effective labor supply is a CES aggregate of three education types: less than secondary ($e = 1$), completed secondary ($e = 2$), and any post-secondary ($e = 3$). In the first layer of the nest, total effective labor supply, $L$, is a CES aggregate of effective labor supplied by workers with and without post-secondary schooling ($L_3$ and $L_{-3}$ respectively):

$$L = \left( \alpha_3 L_3^{\frac{\sigma_3-1}{\sigma_3}} + \alpha_{-3} L_{-3}^{\frac{\sigma_3-1}{\sigma_3}} \right)^{\frac{\sigma_3}{\sigma_3-1}} \tag{2}$$

where $\sigma_3$ is the elasticity of substitution between workers with and without post-secondary and $\alpha_3$ is the relative productivity of workers with post-secondary, standardized so that $\alpha_3 + \alpha_{-3} = 1$ and any common factor is absorbed by $A$. In the next layer of the next, effective labor supplied by workers without post-secondary, $L_{-3}$, is a CES aggregate of effective labor

supplied by workers with and without completed secondary ($L_2$ and $L_1$ respectively):

$$L_{-3} = \left( \alpha_2 L_2^{\frac{\sigma_2-1}{\sigma_2}} + \alpha_1 L_1^{\frac{\sigma_2-1}{\sigma_2}} \right)^{\frac{\sigma_2}{\sigma_2-1}} \tag{3}$$

where $\sigma_2$ is the elasticity of substitution between workers with and without completed secondary and $\alpha_e$ is the relative productivity of group $e$, again standardized so that $\alpha_1 + \alpha_2 = 1$.

Finally, each education-specific effective labor supply is a CES combination of the total number of native ($n$) and migrant ($m$) workers within the education group:

$$L_e = \left( \alpha_{em} L_{em}^{\frac{\sigma_{em}-1}{\sigma_{em}}} + \alpha_{en} L_{en}^{\frac{\sigma_{em}-1}{\sigma_{em}}} \right)^{\frac{\sigma_{em}}{\sigma_{em}-1}} \tag{4}$$
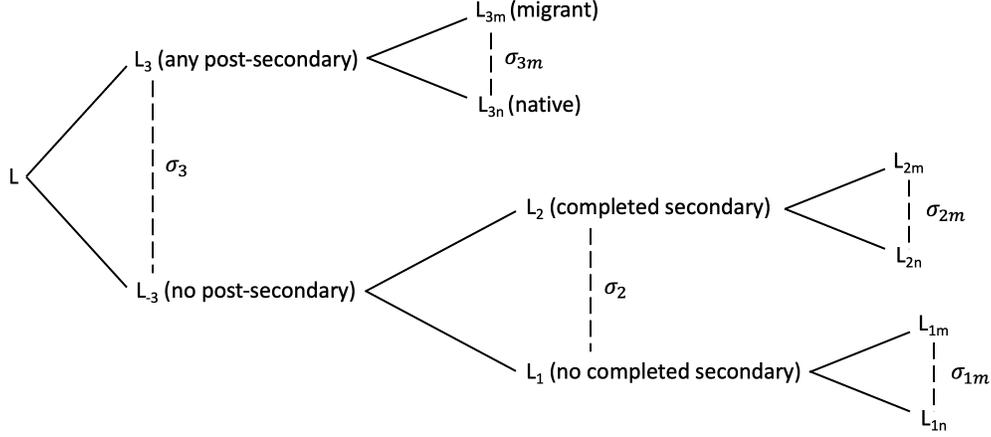
where the elasticity of substitution between migrants and natives $\sigma_{em}$ is allowed to vary by education group. The productivity parameters are again standardized such that $\alpha_{em} + \alpha_{en} = 1$. The nesting structure is presented in Figure 5.

I use these broad education groups to maintain a large enough sample within each cell. Only a very small share of the population did not complete primary or began post-secondary but dropped out. Why do I nest education groups in this order? Existing research indicates that the chosen nesting structure can affect the predicted wage effects of migration (Ottaviano & Peri, 2012). In Section A5, I estimate a generalized production function that allows the substitutability parameters to vary across all education group pairs. While results are imprecise, I find that native substitutability between education groups 1-3 and 2-3 are comparable, while substitutability between groups 1-2 is substantially higher. This motivates treating groups 1 and 2 within a lower level of the nest. Importantly, this is also the structure typically used in Latin America, allowing me to compare estimates of $\sigma_2$ and $\sigma_3$ with the existing literature.

Under perfect competition, wages are set equal to the marginal product of labor, generating the following wage equation by nativity status $j \in \{m, n\}$ and education groups $e \in \{1, 2\}$:

$$\ln W_{ej} = \ln \left( A K^{1-\zeta} \zeta \right) + \ln \alpha_{-3} + \ln \alpha_e + \ln \alpha_{ej} + \left( \zeta - 1 + \frac{1}{\sigma_3} \right) \ln L$$
$$+ \left( \frac{1}{\sigma_2} - \frac{1}{\sigma_3} \right) \ln L_{-3} + \left( \frac{1}{\sigma_{em}} - \frac{1}{\sigma_2} \right) \ln L_e - \frac{1}{\sigma_{em}} \ln L_{ej} \tag{5}$$

16

Figure 5: CES Nesting Structure



and for $e = 3$:

$$\ln W_{3j} = \ln\left(AK^{1-\zeta}\zeta\right) + \ln\alpha_3 + \ln\alpha_{3j} + \left(\zeta - 1 + \frac{1}{\sigma_3}\right)\ln L + \left(\frac{1}{\sigma_{3m}} - \frac{1}{\sigma_3}\right)\ln L_3 - \frac{1}{\sigma_{3m}}\ln L_{3j} \quad (6)$$

These equations intuitively highlight the determinants of wages in this framework. First, log wages increase linearly in the log of each group-specific productivity parameter. Second, the term $\frac{1}{\sigma_3}\ln L$ reflects the fact that, in a model with imperfect substitutability, all workers benefit from an increase in total output. This benefit is mitigated by the term $(\zeta - 1)\ln L$, which captures the diminishing returns in the labor aggregate when capital is held fixed. In Section 6, I will relax this assumption to observe what happens to predicted wage effects when capital adjusts in the long term. Third, in the case of $e \in \{1, 2\}$, wages are affected by labor supply in the rest of the broad education group, captured by the third-to-last term of equation 5. This term is negative if workers in groups 1 and 2 are closer substitutes with each other than with workers in group 3 ($\sigma_2 > \sigma_3$). Fourth, the second-to-last term in each equation captures the effect of labor supply within one's own education group. Similarly, this term is negative if migrant and native workers within the same education group are closer substitutes than workers between groups 1 and 2 ($\sigma_{em} > \sigma_2$). Intuitively, if the migrant labor supply increases in education group 1, this will have a more detrimental effect on native wages in group 1 if migrants and natives are more substitutable, which equalizes wages between migrants and natives. The effect will be less detrimental if natives in group 1 are closer substitutes with group 2, which would equalize this wage effect across groups 1 and 2. Finally, the final term in each equation captures the fact that wages are decreasing in the labor supply in one's own education-nativity group ($L_{ej}$), and less so as the substitutability

17

between natives and migrants in group $e$ increases.

A major takeaway from this framework is that, because of imperfect substitutability, native wages depend on the labor supply in all education groups, not just one's own. This implies that if migrants are moved to compete with more-educated natives, this does more than mechanically shift competition from low- to high-skill groups; it also adjusts the benefits that workers receive from complementarities across groups. Whether the wage effect of migration is negative or positive for an education group depends on the tradeoff between these across-group and within-group effects.

## 4.2   Estimating Equations and Identification

Taking the ratio of $\ln W_{em}$ and $\ln W_{en}$ using equations (5)-(6) yields the following:

$$\ln \left( \frac{W_{em}}{W_{en}} \right) = \ln \left( \frac{\alpha_{em}}{\alpha_{en}} \right) - \frac{1}{\sigma_{em}} \ln \left( \frac{L_{em}}{L_{en}} \right) \tag{7}$$

This equation can be used to estimate $\sigma_{em}$ using changes in the relative wages and labor supplies of migrants and natives. Intuitively, as migrants and natives become increasingly substitutable, wages equalize across groups as the relative labor supplies change, and the sensitivity of the wage ratio to the labor ratio approaches zero.

This is estimated via OLS with the following regression, where $e$, $c$, and $t$ represent education group, metro area, and year respectively:

$$\ln \left( \frac{W_m}{W_n} \right)_{ect} = \lambda_{ec} - \frac{1}{\sigma_{em}} \ln \left( \frac{L_m}{L_n} \right)_{ect} + \epsilon_{ect} \tag{8}$$

Mean log wages and labor supply (number of workers) within each of the 1,422 education-year-metro groups (3 education groups X 79 metro area X 6 years covering 2014-2019) are calculated among migrants and natives age 15-64, where a migrant is defined as someone who was living in Venezuela 5 years ago.[13] $\sigma_{em}$ is allowed to vary by education group, and

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[13]Hourly wages are calculated for the primary job as past-month income over 4.2 times hours worked in a typical week in the past month, including all overtime, benefits, and other transfers. This is calculated for all workers regardless of self-employment or formality status, and I use the term hourly wages to refer to the hourly earnings of the self-employed. Hourly wages are adjusted for yearly inflation at the national level and residualized from a regression on gender and 10-year-wide age group fixed effects, though this has little effect on the results. Finally, they are winsorized at the top and bottom .5% within each year. Cells are weighted by sample size, and I choose not to use the GEIH sampling weights since the survey is not designed to be representative at this level, but the results are not sensitive to this decision. I use mean log wages, rather than log mean wages, following the discussion in Borjas *et al.* (2012).

in practice this is implemented by estimating equation (8) separately by education group. I hold native labor supply fixed to its 2014 value to mitigate any effects driven by endogenous changes in native employment in response to migration, and I show as a robustness test that this does not affect results. This is consistent with existing evidence that this migration had little-to-no effect on Colombian employment, which motivated the decision to estimate a model focused on the wage margin, in which native employment is fixed and wages react to migration-driven supply shifts along the demand curve (Lebow, 2022; Caruso $et$ $al.$ , 2019; Bonilla-Mejía $et$ $al.$ , 2020).

$\lambda_{ec}$ absorbs all determinants of the wage ratio that are fixed within the metro area and education group, and it is used to construct $\alpha_{em}$ and $\alpha_{en}$.[14] Thus, identification is driven by changes in the wage ratio and labor ratio within metro-education cells over time, and anything that affects the baseline wage ratio (for example, wage discrimination against Venezuelans) will not impact estimates of $\widehat{\sigma_{em}}$ as long as it does not vary over time. Importantly, because equation (8) uses ratios and not levels, any changes in wages that equally affect migrants and natives within the same education-metro-year cell (for example, aggregate productivity shocks) will also not impact estimates of $\widehat{\sigma_{em}}$.[15]

An important consideration for identification is that migrants may sort into locations according to the *migrant-native wage ratio* (as opposed to the traditional concern of sorting according to native wages). To account for this, I construct an instrument using the Colombian-born population in the complete 2005 census (Card & Lemieux, 2001; Tabellini, 2020). Venezuelan enclaves were determined two decades before the onset of the current migration, well before the election of Hugo Chávez, and they are uncorrelated with levels or trends in economic outcomes leading up to the current migration (Goldsmith-Pinkham $et$ $al.$ , 2020). The historical number of Venezuelans was minuscule relative to the recent inflow, and there was very little immigration from Venezuela or any other country before 2014, mitigating the concern discussed in (Jaeger $et$ $al.$ , 2018) regarding serial correlation in economic outcomes. At the same time, these historical flows strongly predict current migrant destinations. The results show a close similarity between the OLS and 2SLS specifications. In section A3, this method is described in more detail, alongside a presentation of 2SLS

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[14]$\widehat{\alpha_{em}} = \frac{e^{\widehat{\lambda_{ec}}}}{1+e^{\widehat{\lambda_{ec}}}}$ and $\widehat{\alpha_{en}} = \frac{1}{1+e^{\widehat{\lambda_{ec}}}}$

[15]Ideally, this regression could also include a time trend to capture trends in demand that differentially affect migrants and natives. In practice, adding year fixed effects substantially reduces power. In Table A3, I show that, when estimating (8) at the level of the entire population (without an education distinction), the inclusion of a linear year trend has a minimal effect on the point estimates but increases the standard errors by a factor of 2.5. In the 2SLS model, the first stage Kleibergen-Paap Wald statistic becomes weak. Thus, while it is not possible to include these controls in the full model, I can at least be confident that they do not change the point estimates in the aggregate sample.

results and standard tests of identification assumptions.

In the final steps of the estimation, I estimate $\sigma_2$ and $\sigma_3$. Armed with the estimates of $\widehat{\sigma_{em}}$, $\widehat{\alpha_{em}}$, and $\widehat{\alpha_{en}}$, I use equation (4) to calculate the education-specific effective labor supplies, calculate group-level wages using the population-weighted mean of migrant and native waves within each group, and estimate the next step of the model:

$$\ln \left( \frac{W_2}{W_1} \right)_{ct} = \lambda_{2,c} + \lambda_{2,t} - \frac{1}{\sigma_2} \ln \left( \frac{L_2}{L_1} \right)_{ct} + \epsilon_{2,ct} \tag{9}$$

Likewise, the estimates from regressions (8) and (9) can now be used to calculate the terms needed to estimate $\sigma_3$:

$$\ln \left( \frac{W_3}{W_{-3}} \right)_{ct} = \lambda_{3,c} + \lambda_{3,t} - \frac{1}{\sigma_3} \ln \left( \frac{L_3}{L_{-3}} \right)_{ct} + \epsilon_{3,ct} \tag{10}$$

The same intuition applies to these equations, in that variation in the ratio of wages and labor supplies is used to identify the substitutability parameters, holding constant metro and year fixed effects. Importantly, because native labor supply is held fixed, these estimates are driven by the arrival of migrants across metro areas and occupations. Though this differs from the typical approach in the literature, I estimate values of $\sigma_2$ and $\sigma_3$ that are very comparable with the literature in Colombia and Latin America.

## 4.3   Incorporating Occupational Downgrading

As it stands, this framework cannot be used to study migrant occupational downgrading because it classifies migrants only according to their education and not their occupation. As I discussed in the introduction, adding a nest for occupation skill group is not feasible given the sample of migrants within each metro area. It would also introduce concerns around endogenous native sorting across occupations. Instead, I keep analysis at the education level and I assign migrants to education groups associated with their observed occupation, thus using their occupation to "downgrade" their education assignment. Specifically, for each occupation, I calculate the share of natives in each education group between 2010-2014. Next, I randomly assign migrants into education groups with a probability equal to these shares for their observed occupation. For example, if a migrant is working in a job in which 70% of natives do not have completed secondary, they will be assigned to this education group with 70% probability. I then estimate the model, repeat this for 100 random assignments, and average the parameter values from each estimation. Standard errors are bootstrapped

with 100 resamples and clustered at the metro level.

To develop the intuition for this approach, imagine a scenario in which a group of college-educated migrants arrive in a city and begin to work in a restaurant (which as previously discussed is an occupation in which natives are 60% without secondary, 27% with completed secondary, and 13% with post-secondary). This will affect the wages of both migrants and natives, and the extent to which it affects the wages of migrants more than natives will inform the degree of migrant-native substitutability. If these migrants are simply split into observed education cells, the estimation will fail to account for the fact that migrants are directly affecting native wages across all groups, in particular those without completed secondary. If instead they are split among each education group using the proportions outlined above, which is what the random assignment procedure achieves, we will correctly estimate the degree of imperfect substitutability between migrants in an occupation and the natives they compete with. The migrant-native substitutability parameters that I estimate are thus conceptually different from those typically estimated in the literature, which abstract away from downgrading and simply estimate substitutability within education groups regardless of the occupations migrants are working (Dustmann *et al.* , 2017). Instead, this approach allows me to study migrant wage effects through their occupation, which determines who they compete with in the workplace. It also leads to an intuitive counterfactual representing migration without occupation downgrading: reassign migrants to their observed education group and observe how this affects the predicted wage effects of migration across the education distribution. This is done in Section 6.

I incorporate one additional consideration into the estimation: educated and uneducated migrants may not have the same productivity within a given occupation. For example, a migrant restaurant worker with post-secondary may be more productive than one without post-secondary. I can investigate this empirically by estimating the education wage premium for migrants and natives across occupation skill levels. Table A2 shows that, controlling for gender, age, year fixed effects, and metro fixed effects, migrants face a substantially smaller education premium than natives in occupations where the modal native worker has no secondary: 9.4% for having completed secondary and 15.2% for any post-secondary, relative to 19.8% and 43.5% respectively for natives. The education wage premia are also smaller for migrants than for natives in higher-skill occupation groups. Though small, these wage premia indicate that the effective labor provided by more-educated migrants is larger. Therefore, I adjust the migrant labor supplies using the estimates from Column 2 of Table A2. For example, if a migrant with post-secondary is assigned to the "less than secondary" group, I multiply their labor supply by 1.152, reflecting the wage premium for post-secondary

migrants in low-skill occupations. In practice, this has little effect on the results, and this can be seen in the final column of Table A2.

A limitation of this framework is that it treats migrant downgrading as driven by exogenous forces and not as an equilibrium outcome of migrant occupational sorting. This is partially motivated by the well-recognized barriers discussed in Section 1 that have effectively closed off access to high-skill occupations for many migrants, including lack of education recognition, occupational licensing, and legal status. As I have shown, there is also a large wage gap between migrants in low- and high-skill occupations, leaving little scope for migrant sorting into low-skill occupations in response to wage opportunities or preferences. Another implication of migrant sorting is that migrants who downgrade may be negatively selected on unobserved skill, and thus not comparable with migrants who do not downgrade. This has implications for my counterfactual simulations which I discuss alongside a sensitivity analysis in Section A6.

# 5  Results

## 5.1  Parameter Estimates

Table 2 shows the estimated elasticities of substitution between migrants and natives within each education group.[16] In the second row I also present the negative inverse of each coefficient, which corresponds to the elasticity of substitution, and I use the Delta method to calculate the standard errors.[17] The estimates imply substitutability parameters of 15.0, 12.9, and 7.3 for those without secondary, completed secondary, and any post-secondary respectively. Intuitively, $\sigma_{3m}$ is smaller than $\sigma_{1m}$ because, as migrants enter high-skill occupations, they affect migrant wages more than native wages more so than when they enter low-skill occupations. $\sigma_{3m}$ is comparable with the migrant-native substitutability of around 5 estimated for recently arrived high-skill workers in the UK (Manacorda *et al.*, 2012). The magnitude of $\sigma_{1m}$ approaches the long-term substitutability estimated in the U.S. of around 20, over only 5 years rather than decades (Ottaviano & Peri, 2012). Higher migrant-native substitutability at the bottom of the skill distribution will inflate the negative wage effect of migration for less-educated natives. This higher substitutability could reflect

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[16]The results presented are the average across 100 random assignments of migrants to education groups. The full distributions of parameter estimates are presented in Figures A1 and A2, and for the most part they are smooth and symmetric.

[17]Directly bootstrapping the inverse coefficient is not possible because it is discontinuous at zero, which generates negative elasticities in extreme resamples.

Table 2: Substitutability Parameter Estimates

| | $-\frac{1}{\sigma_{1m}}$ | $-\frac{1}{\sigma_{2m}}$ | $-\frac{1}{\sigma_{3m}}$ | $-\frac{1}{\sigma_2}$ | $-\frac{1}{\sigma_3}$ |
|---|---|---|---|---|---|
| Parameter Estimates: | -0.067 | -0.078 | -0.137 | -0.293 | -0.868 |
| | ( 0.011) | ( 0.009) | ( 0.027) | ( 0.141) | ( 0.366) |
| | $\sigma_{1m}$ | $\sigma_{2m}$ | $\sigma_{3m}$ | $\sigma_2$ | $\sigma_3$ |
| Parameter Estimates: | 14.97 | 12.90 | 7.32 | 3.42 | 1.15 |
| | ( 2.40) | ( 1.52) | ( 1.43) | ( 1.65) | ( 0.49) |

Means presented from estimation of (8) under 100 random assignments of migrants to education groups. Metro-clustered bootstrapped standard errors with 100 resamples in parenthesis. Standard errors for the inverted coefficients are calculated using the Delta method.

that low-skill occupations tend to be more routine and require less skill specialization. These occupations are also more likely to be informal, which may also increase substitutability.[18]

Table 2 also presents the across-education group substitutability parameters, $\sigma_2$ and $\sigma_3$. Because I hold native labor supply fixed, these estimates are driven by the arrival of migrants across metropolitan areas and occupations. They account for national trends in relative labor demand with the inclusion of year fixed effects. The elasticity of substitution between workers with and without completed secondary, $\sigma_2$, and between workers with secondary and post-secondary, $\sigma_3$, are 3.4 and 1.2 respectively. These are very close to existing estimates from Colombia and other countries in Latin America, despite being estimated with a distinct framework based on migrant arrivals across locations. Across 16 countries in Latin America between 1991-2013, Acosta et al. (2019) estimate values of $\sigma_2$ and $\sigma_3$ of 3.5 and 2 respectively. Over the same period, in Argentina, Brazil, and Chile, Fernández & Messina (2018) estimate values of 2.3 and 1.5. While to my knowledge there are no existing estimates of $\sigma_2$ specifically in Colombia, various papers have estimated values of $\sigma_3$ in Colombia that consistently land between 1.3-1.5 (Medina & Posso, 2010; Santamaría et al. , 2004; Núñez & Sánchez, 1998). Thus, these estimates are very reasonable given the existing literature.

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[18]Ideally, I could test this directly by separately estimating the model between formal and informal workers. However, this type of estimation would present two problems: (1) unlike education, formality status is not fixed for native workers, and endogenous sorting by natives could therefore bias these estimates; (2) fewer than 10% of migrants are in the formal sector, creating a severe concern around measurement error of migrant wages in the formal sector. Better understanding the role that informality plays in the economic consequences of migration is an important area for future research.

Notably, $\sigma_2$ is much smaller than estimates of this parameter in the US, which range from around 30 to perfect substitutability (Ottaviano & Peri, 2012; Card, 2009). That $\sigma_2$ is lower in Latin America may reflect the large socioeconomic gap in secondary school completion, as well as the barriers to entering the formal sector faced by workers without secondary. This implies that, in the developing country context, wage effects of migration among workers without secondary will remain concentrated among these workers.

Finally, in Table 3 I present the estimated productivity parameters averaged across metro areas weighted by population. Intuitively, these are the components of the migrant-native wage gap that are fixed within metro areas over time. In all cases, $\alpha_{em}$ are less than .5. This wage gap is most severe in high-skill occupations, where migrants have a relative productivity weight of .22, reflecting the larger wage penalty that migrants face in these occupations, which could be driven for example by low skill transferability in high-skill occupations. Of course, low values of $\alpha_{em}$ may also reflect other sources of lower wages among migrants, such as employer discrimination, and this should be taken into account when interpreting these parameters.[19] $\alpha_2$ is .55 and $\alpha_3$ is .71, reflecting the relatively higher productivity of educated workers. This will increase the benefit of moving migrants from low- to high-skill occupations in terms of increasing total output.

In Section A4, I estimate an extended version of the model that separately adds a nest for age (over and under 30) or gender. Migrants are assigned to education-age or education-gender groups according to the demographic composition of their occupation, and the remainder of the estimation procedure is identical. I also allow the education-specific migrant-native substitutability parameters to vary across demographic groups and I find that they are similar for each age and gender subgroup. I estimate imperfect substitutability across age groups and high substitutability across gender groups. Thus, while predicted wage effects are similar for men and women, the age-nested model generates interesting results regarding the distribution of wage effects across ages which I discuss in the Section 6.

Finally, in Section A3, I present results based on an instrumental variable strategy to account for migrant locational sorting, which may be correlated with potential changes in the migrant-native *wage ratio*. First, I show that the instrument, which is based on historical Venezuelan population shares in the 2005 census, is uncorrelated with pre-period labor market characteristics or pre-trends in wages, and yet is a strong predictor of Venezuelan migration between 2014-2019. The 2SLS estimates of $\sigma_{1m}$, $\sigma_{2m}$, and $\sigma_{3m}$ are 15.1, 13.0, and

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[19]This has some implications for the counterfactual – if migrants face a larger discrimination penalty in higher skill occupations, then in the counterfactual I under-estimate their increased contribution to output based on their wage, which is suffering from discrimination. The key assumption for the counterfactual is that these additional factors unrelated to productivity are constant across education groups.

Table 3: Productivity Parameters

| | $\alpha_{1m}$ | $\alpha_{2m}$ | $\alpha_{3m}$ | $\alpha_2$ | $\alpha_3$ |
|---|---|---|---|---|---|
| Parameter Estimates: | 0.438 | 0.370 | 0.222 | 0.547 | 0.708 |
| | ( 0.009) | ( 0.008) | ( 0.018) | ( 0.007) | ( 0.009) |

Means of productivity parameters across metro areas estimated in equations (8)-(10), averaged over 100 random assignments of migrants to education groups. Metro-clustered bootstrapped standard errors with 100 resamples in parenthesis.

6.5 respectively - similar to the estimates presented in this section and indicating that such locational sorting is not introducing bias.

## 5.2 Robustness

I conduct various robustness checks in Table 4. First, it may be a concern that migration was heavily concentrated along the Venezuelan border, which may be correlated with economic trends during the period of analysis. During this period, locations near the border underwent changes in economic activity, daily commuting from Venezuela, and exposure to crime driven by armed traffickers and guerrilla organizations. Therefore, I show that results are robust to dropping the six metro areas within 100 km driving distance of the Venezuelan border, which also includes all of the outliers with a migrant share greater than 15% that have the potential to disproportionately drive results.[20] To ensure that changing exposure to trade with Venezuela is not an omitted variable, I also control for net imports and exports to Venezuela at the department level and results do not change.[21] I also drop Bogotá, the largest city in the sample, to ensure it is not single-handedly driving any results. To mitigate concerns around measurement error within small metro areas, I also repeat the estimation on the 23 metro areas for which the GEIH is officially representative. The similarity of results indicates that these largest areas are the main drivers of the estimation.

Another concern regards native internal migration. According to analysis in Lebow (2022), Venezuelan migration induced small increases in out-migration among natives without post-secondary education. This could introduce a bias by endogenously changing the

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[20]Driving distance was calculated using Open Street Maps software, from the central municipality of the metro area to the closest crossing point along the Venezuelan border.

[21]While Venezuela used to be a top trading partner of Colombia, its trade shares steadily declined during the 2000s such that Venezuela represented a very small share of imports and exports in 2010. However, trade may have persisted longer or had lagged economic effects closer to the border. Trade volumes by department origin and destination are publicly provided by DANE.

Table 4: 2SLS Migrant-Native Substitutability - Robustness

| | $\sigma_{1m}$ | $\sigma_{2m}$ | $\sigma_{3m}$ |
|---|---|---|---|
| Drop <100km from Border | 15.16 | 13.12 | 7.34 |
| | ( 2.54) | ( 1.63) | ( 1.47) |
| Control Tade with Venezuela | 15.26 | 12.89 | 7.22 |
| | ( 2.82) | ( 1.55) | ( 1.22) |
| Drop Bogotá | 15.77 | 14.78 | 9.15 |
| | ( 2.94) | ( 1.80) | ( 1.54) |
| Restrict to 23 Official Metro Areas | 15.11 | 14.04 | 7.72 |
| | ( 3.12) | ( 1.90) | ( 1.72) |
| Natives Assigned to Previous Location | 14.62 | 13.38 | 7.56 |
| | ( 2.33) | ( 1.53) | ( 1.50) |
| Native Population not Fixed to 2014 | 16.50 | 12.73 | 7.35 |
| | ( 3.89) | ( 2.09) | ( 1.73) |
| Drop Wages of Recent Migrants | 25.54 | 19.39 | 9.62 |
| | ( 7.70) | ( 4.10) | ( 2.68) |
| Only Male | 15.29 | 13.25 | 6.36 |
| | ( 2.46) | ( 1.48) | ( 1.02) |
| Only Age>24 | 11.03 | 10.58 | 6.56 |
| | ( 1.45) | ( 1.25) | ( 1.41) |
| Only Informal | 19.99 | 25.54 | 13.28 |
| | ( 4.15) | ( 5.56) | ( 3.32) |
| Only Full-Time | 15.29 | 12.07 | 7.01 |
| | ( 3.75) | ( 1.95) | ( 1.85) |
| All Working Age | 15.19 | 13.21 | 7.40 |
| | ( 2.49) | ( 1.58) | ( 1.40) |
| No Productivity Adjustment | 14.75 | 12.68 | 7.01 |
| | ( 2.34) | ( 1.47) | ( 1.32) |

See notes to Table 2.

composition of native wages across metro areas. As a robustness check, I assign all natives to their metro area of residence 5 years before each survey year, thus holding native composition fixed to the pre-migration period. The results do not change. This is not surprising given the small magnitude of effects on internal migration. I also show that the decision to hold the native labor supply fixed does not have a large effect on the estimation.

It is also possible that the changing composition of migrants arriving over this period is driving changes in the migrant-native wage ratio. I have already residualised wages from age and gender. To understand if other unobserved characteristics are driving a compositional effect, I set the wages of migrants who arrived in the past year to missing, so that very recently arrived migrants impact the labor supply but not the migrant wage. When I do this, the standard errors increase substantially, reflecting the large number of wage observations that

are dropped. The substitutability parameters increase, especially for workers in the lower education groups. Therefore, absent compositional change, migrant-native substitutability is if anything larger than I estimate, and the gradient across education groups is even steeper.

Next, there is the concern that migration may be inducing changes in native employment, which could also create a compositional change in native wages. While there is evidence that this migration had little effect on native employment, there is some evidence that it decreased employment among subgroups including workers under age 25, formal sector workers, and women (Lebow, 2022; Delgado-Prieto, 2022; Pedrazzi & Penaloza-Pacheco, 2022; Otero-Cortés *et al.* , 2022). As a robustness test, I drop these subgroups from the analysis. Restricting the sample to men or to workers under age 25 has little effect on results.[22] Restricting the sample to informal workers increases the estimated substitutability parameters, but the standard errors increase as well, and the gradient across more and less educated workers remains. I can further reduce concerns regarding endogenous labor supply by restricting the analysis to full-time workers or by replacing employment on the right-hand side with the total working-age population.

Finally, to build confidence in the random assignment procedure, I show in Table A4 that results are similar when I instead assign migrants to the median or modal education in their occupation. The estimate of $-\frac{1}{\sigma_{2m}}$ is less precise, reflecting the fact that fewer than 10% of the population is in an occupation where the modal person has completed secondary.

# 6    Total Wage Effects of Migration

I now use the estimated parameters to calculate the total wage effects of migration. We can use equations (5) and (6) to express the wage change for natives as a function of the change in migrant labor supply while holding the native supply fixed. For $e \in \{1, 2\}$,

$$d\ln W_{en} = \left(\zeta - 1 + \frac{1}{\sigma_3}\right) d\ln L + \left(\frac{1}{\sigma_2} - \frac{1}{\sigma_3}\right) d\ln L_{-3} + \left(\frac{1}{\sigma_{em}} - \frac{1}{\sigma_2}\right) d\ln L_e \qquad (11)$$

and for $e = 3$,

$$d\ln W_{3n} = \left(\zeta - 1 + \frac{1}{\sigma_3}\right) d\ln L + \left(\frac{1}{\sigma_{3m}} - \frac{1}{\sigma_3}\right) d\ln L_3 \qquad (12)$$

Labor supply at the national level is calculated as the number of metro area workers

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[22]Migrants over age 24 also completed schooling in Venezuela before the onset of the crisis, limiting concerns that younger workers received lower-quality schooling and this affects the results.

aged 15-64 in the GEIH using the appropriate survey weights. The baseline education group-specific labor supply, $L_e$, is calculated using equation (4), where $L_{em}$ is the 2014 migrant population (those who arrived from Venezuela since 2009) and $L_{en}$ is the 2014 native population. The log change in this labor supply, $d\ln L_e$, is the change in the log of this term when $L_{em}$ is replaced with the migrant population in 2019. $L_{-3}$ and $L_3$ are calculated in the same way using equations (2) and (3). As in the estimation, migrants are assigned to education groups according to the education distribution of natives in their occupation. For example, if natives in an occupation are evenly split between education groups 1 and 2, then 50% of migrants in that occupation are assigned to each of these groups.

An important component of equations (11) and (12) is the term $(\zeta - 1)\,d\ln L$, which captures the role of diminishing returns in the labor aggregate when capital is held fixed. In this framework, if capital is fully flexible, it is generally not possible for migration to generate a non-trivial wage effect for the population average, because output becomes linear in the labor aggregate.[23] By holding capital fixed, I allow for negative average wage effects in the short term. Especially considering that the majority of migrants did not arrive until 2018, it is reasonable to think that capital has not had adequate time to respond to the increase in labor supply in Colombia. I set $\zeta = .49$, which is the preferred labor share for Colombia reported by the Penn World Tables (averaged across 2014-2019, though it is relatively stable over this period).[24] Because capital is skill-neutral, this parameter determines the magnitude of the average wage effect but not the wage distribution, which is driven by differences in competition faced in each education group and the within- and across-group elasticity parameters. In Section A6, I demonstrate that varying $\zeta$ shifts wages equally for all education groups, and within plausible ranges of $\zeta$ between .4-.6, has little effect on their magnitudes. I will also explore how wages change as capital adjusts in the long term, which for the same reason affects the average wage but not the wage distribution.

Column 1 of Table 5 shows the total changes in labor supply, change in "effective" labor supply at each level of the nest, and change in native wages by education group. The total growth in the population due to migration over this period is 6.2% when restricted to the sample of urban workers aged 15-64. Under downgrading, the without secondary, with secondary, and with post-secondary education groups experience a 7.9%, 6.2%, and 3.9% increase in labor supply respectively. Column 5 shows the associated predicted wage effects

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[23]See Ottaviano & Peri (2008) for an extensive discussion of the role of capital flexibility in this framework.

[24]The biggest challenge with measuring the labor share in Colombia is that self-employment income includes a combination of labor and capital income. The method used here assumes that self-employed workers use labor and capital in the same proportion as the rest of the economy. Methods that impute self-employment labor shares according to observables predict similar values over this period (Gomis, 2019).

of -4.1%, -3.4%, and -0.3%. Standard errors are generated by simulating 1,000 draws from a joint normal distribution with the estimated means and standard errors for each parameter. These wage effects broadly mirror the non-structural estimates from Lebow (2022), indicating that the model does a reasonably good job of replicating those results.[25]

I now consider a counterfactual in which I reassign migrants to their observed education group rather than the one assigned according to their observed occupation. This can be thought of as a policy counterfactual in which there is no migrant downgrading relative to natives in their education group. The results are presented in Panel B of Table 5. Without downgrading, the labor supply increase shifts substantially towards education groups 2 and 3: it decreases by 2.7pp in group 1, and increases by 2.1pp and 1.7pp in groups 2 and 3 respectively. The wage decrease faced by natives in group 1 reduces from -4.1% to -3.1%. On the other hand, the wage effect for natives with completed secondary remains almost unchanged, despite this group facing a substantial increase in competition. There is a small increase in the wage effect for post-secondary workers, from -.3% to -.7%. For visualization, these effects are plotted with 95% confidence intervals in Figure A4a. Finally, a measure of inequality is the wage gap between natives with post-secondary and without completed secondary. In 2014, these hourly wages were $4.00 and $1.15 respectively in 2018 USD (GEIH). The model predicts that 2014-2019 Venezuelan migration increased this wage gap from 347% to 361% and that in the absence of migrant downgrading, it would have increased only to 356%, thus reducing the effect of migration on this inequality measure by 36%.

Why does the increase in within-group labor supply not substantially reduce wages for workers with completed secondary and post-secondary education? To understand this, in Figure A3 I separately plot the components of equations (11) and (12). Among natives without completed secondary, there is a .53 increase in log wages from moving migrants out of their specific education group, a .26 increase from moving migrants out of the broad education group, and a .14 increase from the increase in total "effective" labor supply, which according to Table 5 increases from 3.2% to 3.6%. This demonstrates that as migrants are moved into higher-productivity occupations, the increase in total output increases everyone's marginal product. For natives with completed secondary, the increase in competition within the specific education group is counteracted by the reduction in competition in the broad

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[25]Specifically, Lebow (2022) estimates average native wage effects from a 1pp increase in the total migrant share of -1.42%, -.86%, and -.75% for natives with less than secondary, secondary, and post-secondary respectively. Scaling this by the 5.8pp increase in the migrant share seen in the sample over this period, this corresponds to respective wage decreases of -8.24% [-10.85,-5.63], -4.99% [-7.48,-2.49], and -4.35% [-8.64,-0.06], with 95% confidence intervals in brackets. Thus, the non-structural wage effects for natives with less than secondary are larger in magnitude than those predicted by the nested-CES model, and this is even more true for post-secondary natives. But the broad pattern across education groups is replicated.

Table 5: Total Effect of Immigration on Native Wages

| | % Change in Labor Supply | $\Delta L_e$ $(e \in 1, 2, 3)$ | $\Delta L_e$ $(e \in m3, 3)$ | $\Delta L$ | $\Delta ln(W_{en})$ Fixed K | $\Delta ln(W_{en})$ Flexible K |
|---|---|---|---|---|---|---|
| **Panel A: Under Downgrading** | | | | | | |
| Less than Secondary | 7.90 | 7.73 | 6.25 | 3.17 | -4.05 ( 0.12) | -2.46 ( 0.20) |
| Completed Secondary | 6.16 | 4.79 | 6.25 | 3.17 | -3.38 ( 0.12) | -1.79 ( 0.20) |
| Post-Secondary | 3.88 | 1.94 | 1.94 | 3.17 | -0.29 ( 0.09) | 1.30 ( 0.07) |
| **Panel B: No Downgrading Counterfactual** | | | | | | |
| Less than Secondary | 5.24 | 5.24 | 5.76 | 3.57 | -3.12 ( 0.13) | -1.33 ( 0.25) |
| Completed Secondary | 8.21 | 6.27 | 5.76 | 3.57 | -3.28 ( 0.13) | -1.49 ( 0.25) |
| Post-Secondary | 5.62 | 2.69 | 2.69 | 3.57 | -0.68 ( 0.12) | 1.10 ( 0.08) |

Percent change in total labor supply, effective labor supply, and native wages due to migration from Venezuela between 2014-2019. In Panel A, migrants are assigned to education groups according to native education shares in their occupation (as in the estimation). In Panel B, migrants are assigned to their observed education (the counterfactual). Standard deviation are based on 1,000 simulations with parameters drawn from a joint normal distribution of the estimated means and standard errors.

education group and the increase in total output. For natives with post-secondary, the large increase in within-group competition is mitigated by the increase in total output by 26%. Thus, the increase in total output plays an important role in mitigating the increase in competition for more-educated workers.

Two interesting facts about the estimated parameters may have important implications for the results being discussed. First, migrants and natives are less substitutable in high-skill occupations, such that undoing downgrading moves migrants into occupations where they have a lower marginal effect on native wages. Second, the low substitutability across education groups in Colombia segments the economy such that wage changes are more concentrated among education groups, increasing the consequences of migrant downgrading for less-educated natives. To test the importance of these factors, in Table A5 I estimate wage effects under alternate parameter scenarios. First, in Panel B I set each migrant-native substitutability parameter to 10, approximately the substitutability for the population average in Table A3. The consequences of migration and downgrading are mostly unchanged, indicating that this factor is relatively unimportant.[26] In Panel C, I increase $\sigma_2$ to 30 and $\sigma_3$ to

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[26]In fact, the average wage effect for low-education natives is *more negative* as $\sigma_{1m}$ decreases, even though

2, approximately the values estimated in the U.S. (Ottaviano & Peri, 2012; Card, 2009; Katz & Murphy, 1992). The wage effect under downgrading for natives without secondary reduces from -4.1% to -2.6%, and the gain from undoing downgrading for low-skill workers reduces by around 80%.[27] This demonstrates that low across-education substitutability, in particular across workers with and without completed secondary, severely amplifies the consequences of migrant downgrading for less-educated natives, and this is a common characteristic of developing country labor markets (Acosta *et al.* , 2019; Fernández & Messina, 2018).

Thus far, I have discussed wage effects under fixed capital. In the final column of Table 5 (and in Figure A4b), I show the wage effects with and without downgrading while allowing capital to fully adjust at a rate proportional to the growth in aggregate effective labor supply. Full capital adjustment increases wages equally for all education groups because capital is skill-neutral, and it makes the average wage effect for natives slightly positive due to the imperfect substitutability between migrants and natives (Amior & Manning, 2020; Borjas, 1995). Existing evidence indicates that this tends to take around 5-10 years, which is how long average wages typically recover from supply-induced wage decreases (Verme & Schuettler, 2021; Edo, 2020). The wage effect by education group becomes -2.5%, -1.8%, and 1.3% for workers without completed secondary, with completed secondary, and with post-secondary respectively. Absent downgrading, these numbers change to -1.3%, -1.5%, and 1.1%, demonstrating that the distributional benefits of undoing downgrading persist in the long term. For natives without completed secondary, the wage costs of migrant downgrading increase from approximately 30% to 80%.

I also calculate that migration increases total output by 1.5% and 1.7% with and without migrant downgrading respectively. As capital adjusts, these rise to 3.2% and 3.6%, proportional to the increase in effective labor supply because this is a constant-returns-to-scale model. Capital growth matches the larger increase in effective labor supply, increasing the benefits of undoing downgrading for total output in the long term.

the marginal effect of within-group competition governed by $\left(\frac{1}{\sigma_{1m}} - \frac{1}{\sigma_2}\right)$ is less negative. This is because there is an additional effect of decreasing $\sigma_{em}$: under the CES structure, the migration-driven increase in effective labor supply $L_1$ becomes larger as migrants and natives are less substitutable, thus making the total wage effect for education group 1 more negative. This effect is relatively more important when the baseline number of migrants is small, as is the case here, and it counteracts the reduction in the marginal effect of competition. The reverse happens to high-education natives as $\sigma_{3m}$ increases.

[27]In Section A6, I explore the effect of varying $\sigma_2$ and $\sigma_3$ around plausible ranges in the literature, to demonstrate that only for large increases in these parameters close to the values observed in the U.S. do they begin to notably change the results.

## 6.1   Effect on Migrant Wages

Given the imperfect substitutability between migrants and natives, migration will have a larger detrimental effect on the wages of migrants. This is shown in Table A6. The effect of migration on migrant hourly wages in occupations that tend to employ less than secondary, completed secondary, and post-secondary workers is -24.8%, -26.8%, and -40.7% respectively. In other words, a migrant with less than secondary earns 24.8% less than they would if no other migrants arrived over this period. The larger consequences for migrants in high-skill occupations reflect the lower migrant-native substitutability in these occupations, which benefits natives at the expense of migrants. If $\sigma_{3m}$ increases to 10, the wage effect in the post-secondary group falls in magnitude from -40.7% to -29.7%, demonstrating how sensitive migrant wages are to the degree of migrant-native imperfect substitutability. In the counterfactual, moving migrants into high-skill occupations further shifts competition towards high-skill migrants and the consequences for migrants in high-skill occupations are amplified by the lower migrant-native substitutability in this group.[28]

Undoing migrant downgrading will affect migrant wages directly by moving migrants into higher-wage occupations, and indirectly through the equilibrium wage effects discussed in the previous paragraph. I calculate that migrant wages increase 11.2% on average under the counterfactual. If I turn off the equilibrium wage response by holding group-specific wages fixed, this increases to 14.1%, highlighting the importance of considering general equilibrium wage effects when calculating the effects of downgrading on migrant wages.

## 7   Conclusion

In this paper, I estimate a nested-CES production function with imperfect substitutability between migrants and natives and migrant occupational downgrading. I use the model to quantify the effect of Venezuelan migration on native Colombian hourly wages and how it would change in the absence of migrant occupational downgrading. I find that absent migrant downgrading the increase in labor supply faced by workers without completed secondary falls from 7.9% to 5.2%, and their reduction in wages falls from -4.1% to -3.1%. At the same time, it induces little change in the wages of more-educated natives. This is primarily explained by the increase in total productivity under the reallocation, which benefits all workers. Thus, migrant downgrading has important consequences for both the wage distribution and aggregate productivity, and these effects persist under long-term capital

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[28]Panel B of Table A6 demonstrates that allowing for flexible capital increases wages by the same amount for migrants and natives, but this effect is smaller relative to the large magnitude of migrant wage effects.

adjustment. The results highlight the importance of labor market policies to address migrant downgrading, not only to benefit migrants but also to mitigate effects on native wage inequality and to maximize productivity.

I also find that low substitutability across education groups, in particular between workers with and without completed secondary schooling, inflates the consequences of migrant downgrading for native wage inequality. Given that this is a common characteristic of developing countries, the majority of forced displacement flows to developing countries, and forcibly displaced migrants face a high risk of downgrading, policies to address migrant downgrading are particularly important in the developing country setting.

A limitation of this analysis is that I do not observe the previous occupations of migrants before leaving Venezuela, so I am unable to estimate the match-specific productivity gains from placing migrants into occupations where they have the most experience. This is an interesting avenue for future research if such data becomes available. I also do not study the specific barriers that prevent migrants from entering high-skill occupations, and better understanding these barriers is crucial to inform migration policy. I do not account for the demand-side benefits of migrant consumption, which will increase the benefits of undoing migrant downgrading as migrant incomes improve, and I see my results as likely a lower bound on the benefits of policies to reduce downgrading. Finally, I studied this migration under a relatively short time horizon, and there are various channels not explicitly included in the model that may increase the benefits of such policies over time, such as industry-specific knowledge transfer, the productivity benefits of diversity, and the establishment of cross-country business networks. Researchers should continue to study the myriad of ways in which this mass migration will affect the Colombian labor market over the coming decades.

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# A1 Additional Tables and Figures

## Table A1: Sample Statistics

| | Non-Migrants | | | | | | Migrants | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
| **All Working-Age (Age 15-64)** | | | | | | | | | | | | |
| N | 380,468 | 381,579 | 378,484 | 373,135 | 368,902 | 360,745 | 1,262 | 1,891 | 3,635 | 6,537 | 13,690 | 20,554 |
| Male (%) | 48.0 | 48.0 | 48.1 | 48.1 | 48.1 | 48.0 | 58.7 | 52.9 | 53.6 | 50.8 | 50.9 | 49.6 |
| Age | 38.7 | 38.8 | 38.9 | 39.0 | 39.2 | 39.4 | 34.5 | 35.3 | 34.2 | 33.2 | 32.2 | 32.1 |
| Completed Secondary (%) | 29.2 | 31.0 | 32.4 | 33.7 | 34.2 | 35.1 | 30.3 | 28.5 | 28.1 | 33.5 | 36.8 | 37.7 |
| Any Post-Secondary (%) | 26.1 | 25.5 | 26.1 | 26.2 | 27.3 | 27.7 | 18.1 | 20.3 | 19.0 | 24.3 | 25.2 | 24.5 |
| Labor Force Participation (%) | 79.4 | 79.7 | 79.8 | 79.5 | 79.1 | 78.8 | 79.4 | 81.0 | 81.0 | 82.2 | 84.2 | 81.8 |
| Unemployment Rate (%) | 9.4 | 9.3 | 9.6 | 10.0 | 10.2 | 10.9 | 12.6 | 10.9 | 17.0 | 14.9 | 15.0 | 14.7 |
| Employed (%) | 72.0 | 72.3 | 72.1 | 71.5 | 71.0 | 70.3 | 69.5 | 72.2 | 67.2 | 70.0 | 71.6 | 69.8 |
| **Employed** | | | | | | | | | | | | |
| Male (%) | 56.4 | 56.3 | 56.4 | 56.4 | 56.5 | 56.6 | 69.5 | 64.9 | 65.0 | 61.2 | 61.4 | 60.7 |
| Age | 38.5 | 38.6 | 38.7 | 38.8 | 39.0 | 39.3 | 33.5 | 35.3 | 34.3 | 33.6 | 32.7 | 32.4 |
| Completed Secondary (%) | 29.2 | 31.3 | 32.6 | 33.7 | 34.1 | 34.9 | 29.2 | 26.8 | 28.9 | 33.2 | 36.9 | 38.2 |
| Any Post-Secondary (%) | 28.7 | 27.8 | 28.3 | 28.3 | 29.5 | 30.7 | 20.5 | 19.0 | 20.9 | 26.3 | 26.8 | 26.8 |
| Ln(Hourly Earnings) | 8.38 | 8.37 | 8.37 | 8.39 | 8.41 | 8.42 | 8.24 | 8.21 | 8.13 | 8.09 | 7.97 | 7.97 |
| Ln(Hours per week) | 3.77 | 3.76 | 3.77 | 3.77 | 3.76 | 3.76 | 3.84 | 3.73 | 3.80 | 3.84 | 3.85 | 3.84 |
| Own-Account (%) | 40.3 | 39.6 | 39.1 | 38.9 | 39.4 | 39.0 | 44.4 | 50.5 | 49.7 | 47.1 | 48.1 | 46.8 |
| Formal (%) | 41.6 | 42.8 | 44.4 | 45.7 | 46.4 | 47.2 | 34.0 | 22.1 | 18.1 | 21.2 | 13.3 | 12.4 |
| Mean Yrs Educ in Occup | 9.6 | 9.6 | 9.6 | 9.6 | 9.7 | 9.8 | 8.7 | 8.7 | 8.6 | 8.7 | 8.6 | 8.6 |

Sample restricted to residents of 79 primary metro areas, age 15-64, with completed education. A migrant is defined as anyone who was living in Venezuela 5 years before the survey. Source: GEIH, population weights applied.

Table A2: Education Wage Premia by Occupation Skill Group

| | Non-Migrants | Migrants |
|---|---|---|
| **Occupation Mode: Not Completed Secondary** | | |
| Not Completed Secondary | (excluded) | (excluded) |
| Completed Secondary | 19.82*** | 9.37*** |
| | (0.15) | (0.89) |
| Any Post-Secondary | 43.52*** | 15.22*** |
| | (0.24) | (1.18) |
| **Occupation Mode: Completed Secondary** | | |
| Not Completed Secondary | (excluded) | (excluded) |
| Completed Secondary | 32.29*** | 11.57*** |
| | (0.51) | (3.39) |
| Any Post-Secondary | 59.13*** | 19.30*** |
| | (0.63) | (4.23) |
| **Occupation Mode: Any Post-Secondary** | | |
| Not Completed Secondary | (excluded) | (excluded) |
| Completed Secondary | 38.99*** | 17.54*** |
| | (0.52) | (4.83) |
| Any Post-Secondary | 100.98*** | 49.91*** |
| | (0.50) | (4.69) |

Outcome is 100 times log hourly wage. Controlling age group (5-year bins), gender, year FE and metro FE. Restricted to urban workers age 15-64. Source: GEIH.

Table A3: Population Average Migrant-Native Substitutability with Time Trend

|  | OLS | | 2SLS | |
|---|---|---|---|---|
|  | (1) | (2) | (3) | (4) |
| Migrant-Native Log-Ratio | -0.115 | -0.108 | -0.112 | -0.522 |
|  | ( 0.020) | ( 0.050) | ( 0.016) | ( 0.792) |
| Kleibergen-Paap Wald stat |  |  | 88.84 | 0.46 |
| Metro FE | X | X | X | X |
| Year Trend |  | X |  | X |

$-\frac{1}{\sigma_m}$ is estimated using equation (8) for all education groups combined. Metro-clustered standard errors in parenthesis. Kleibergen-Paap Wald statatic is clustered at the metro level.

Table A4: Alternate Migrant Education Assignment Mechanisms

|  | $\sigma_{1m}$ | $\sigma_{2m}$ | $\sigma_{3m}$ |
|---|---|---|---|
|  | **Median Native Education** | | |
| Parameter Estimates: | 14.49 | 12.82 | 6.71 |
|  | ( 5.04) | ( 3.29) | ( 2.70) |
|  | **Modal Native Education** | | |
| Parameter Estimates: | 14.71 | 20.83 | 6.33 |
|  | ( 4.76) | ( 20.40) | ( 2.20) |

Equation (8) is estimated with migrants assigned to the median or the modal education group among natives in their occupation between 2010-2015. Metro-clustered standard errors in parenthesis.

## Figure A1: Substitutability Parameter Distributions
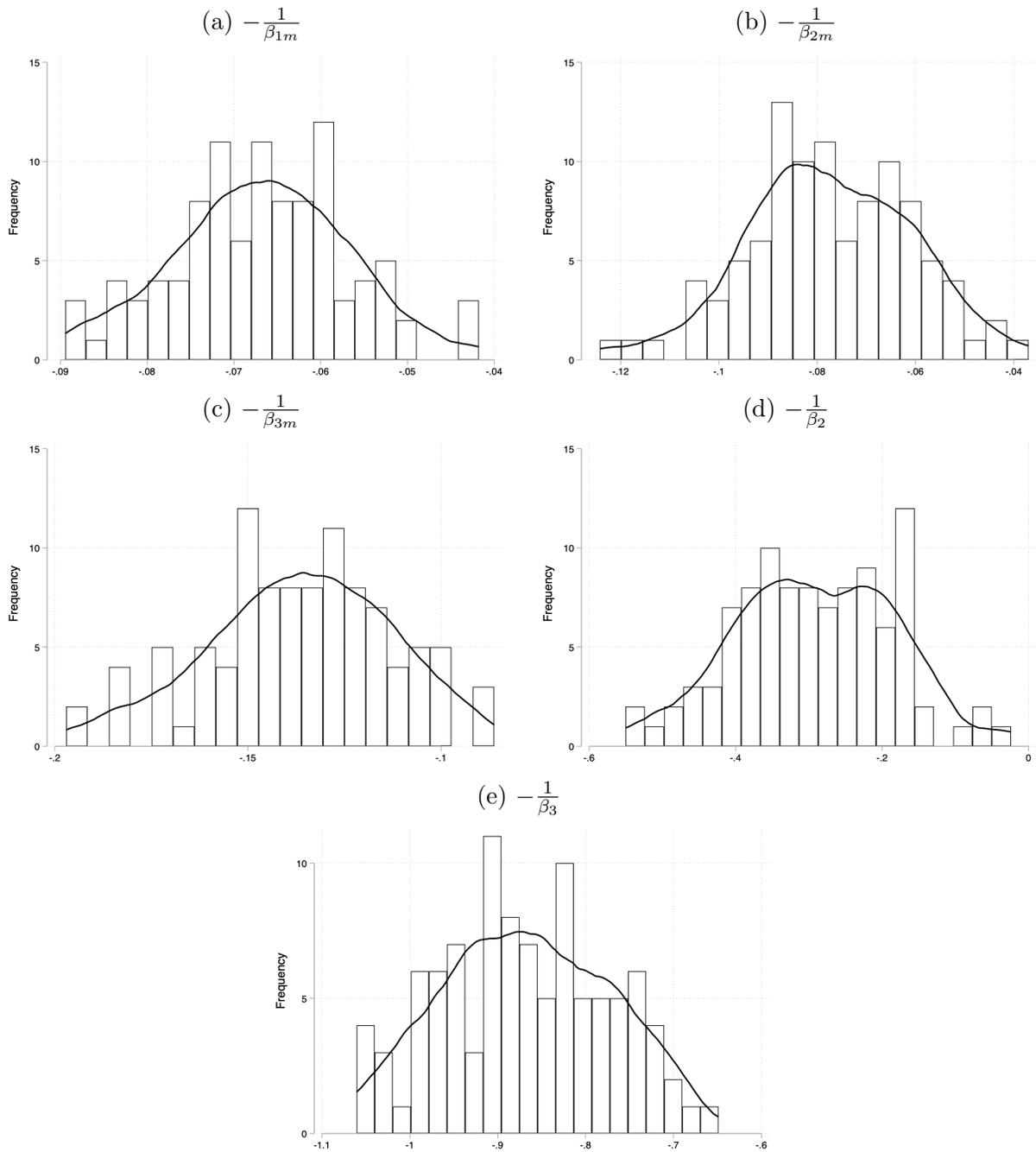
### (a) $-\frac{1}{\beta_{1m}}$



### (b) $-\frac{1}{\beta_{2m}}$



### (c) $-\frac{1}{\beta_{3m}}$



### (d) $-\frac{1}{\beta_2}$



### (e) $-\frac{1}{\beta_3}$



The coefficient from each of 100 random assignments is presented alongside an Epanechnikov kernel density plot.

# Figure A2: Productivity Parameter Distributions
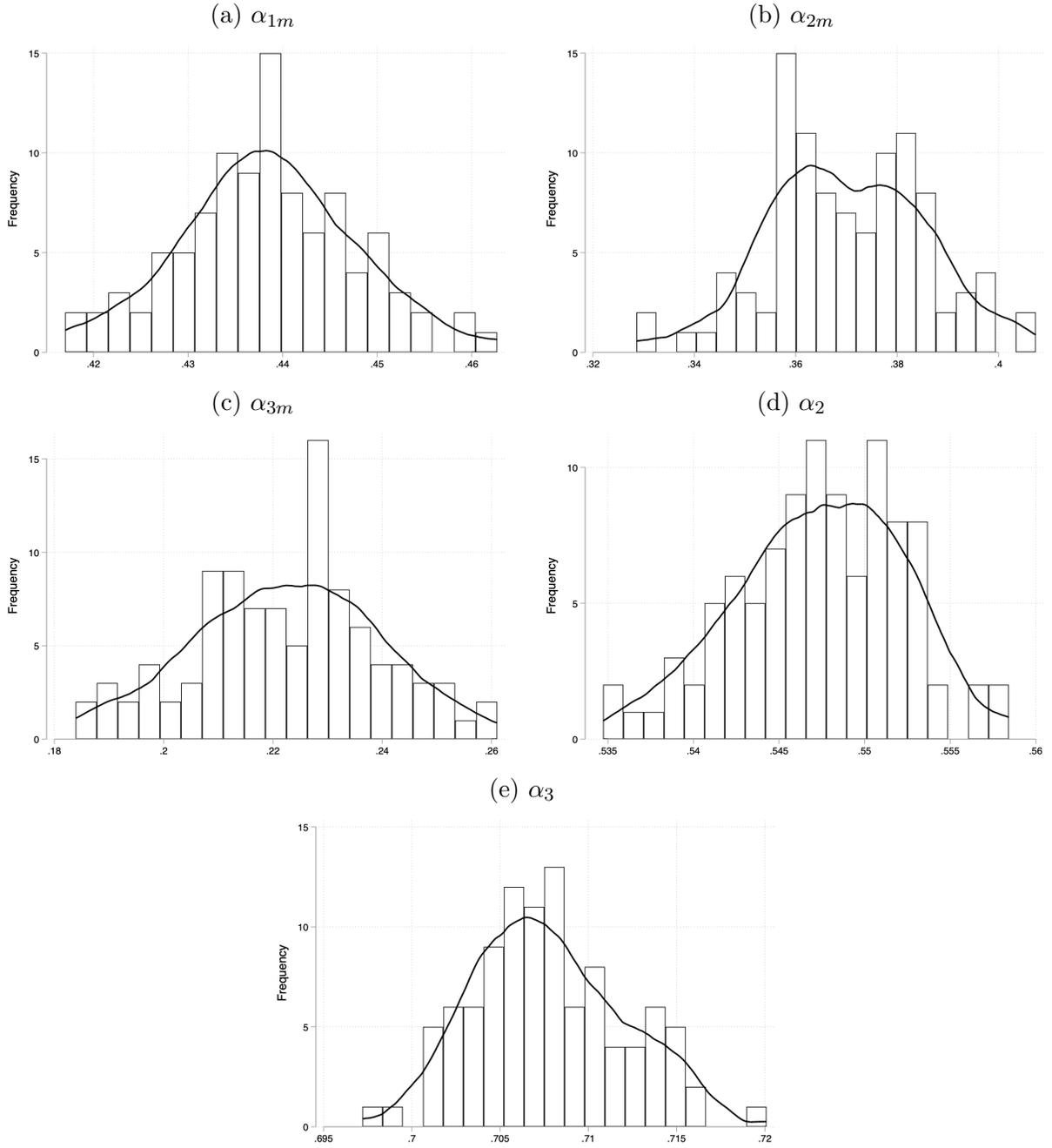
(a) $\alpha_{1m}$

(b) $\alpha_{2m}$

(c) $\alpha_{3m}$

(d) $\alpha_2$

(e) $\alpha_3$

The coefficient from each of 100 random assignments is presented alongside an Epanechnikov kernel density plot.

## Figure A3: Decomposition of Change in Log-Wage under Counterfactual
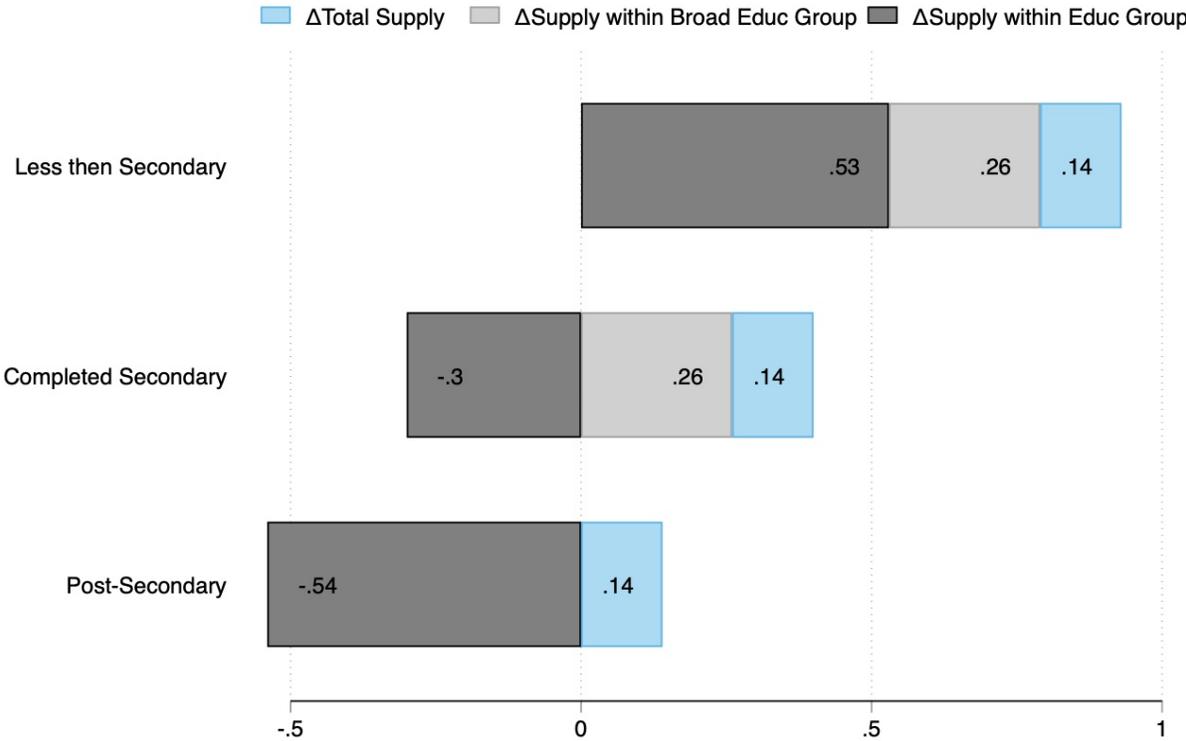


Terms of equation (11) and (12) are separately plotted. The first term in both equations, $\left(\zeta - 1 + \frac{1}{\sigma_3}\right) d\ln L$, is in light-blue. The second term in equation (11), $\left(\frac{1}{\sigma_2} - \frac{1}{\sigma_3}\right) d\ln L_{-3}$, is in light gray. The final term, $\left(\frac{1}{\sigma_{em}} - \frac{1}{\sigma_2}\right) d\ln L_e$, is in dark gray.

Table A5: Total Wage Effects using Alternate Parameter Values

| | Panel A: Original Parameter Values | | |
| --- | --- | --- | --- |
| | Downgrading | No Downgrading Counterfactual | Difference |
| Less than Secondary | -4.05 | -3.12 | 0.93 |
| | ( 0.12) | ( 0.13) | ( 0.04) |
| Completed Secondary | -3.38 | -3.28 | 0.10 |
| | ( 0.12) | ( 0.13) | ( 0.03) |
| Post-Secondary | -0.29 | -0.68 | -0.40 |
| | ( 0.09) | ( 0.12) | ( 0.03) |
| | Panel B: $\sigma_{1m} = \sigma_{2m} = \sigma_{3m} = 10$ | | |
| | Downgrading | No Downgrading Counterfactual | Difference |
| Less than Secondary | -4.33 | -3.43 | 0.90 |
| | ( 0.18) | ( 0.16) | ( 0.05) |
| Completed Secondary | -3.71 | -3.58 | 0.12 |
| | ( 0.31) | ( 0.26) | ( 0.06) |
| Post-Secondary | -0.16 | -0.55 | -0.39 |
| | ( 0.10) | ( 0.12) | ( 0.03) |
| | Panel C: $\sigma_2 = 30, \sigma_3 = 2$ | | |
| | Downgrading | No Downgrading Counterfactual | Difference |
| Less than Secondary | -2.63 | -2.47 | 0.16 |
| | ( 0.07) | ( 0.07) | ( 0.02) |
| Completed Secondary | -2.67 | -2.37 | 0.30 |
| | ( 0.09) | ( 0.08) | ( 0.02) |
| Post-Secondary | -0.73 | -1.00 | -0.27 |
| | ( 0.06) | ( 0.09) | ( 0.02) |

See notes to Table 5. Panel titles indicate the parameters used. In parenthesis are the standard deviation of 1,000 simulations, with parameters drawn from a joint normal distribution using their estimated means and standard errors.

## Figure A4: Total Wage Effects of Immigration

### (a) No Capital Adjustment
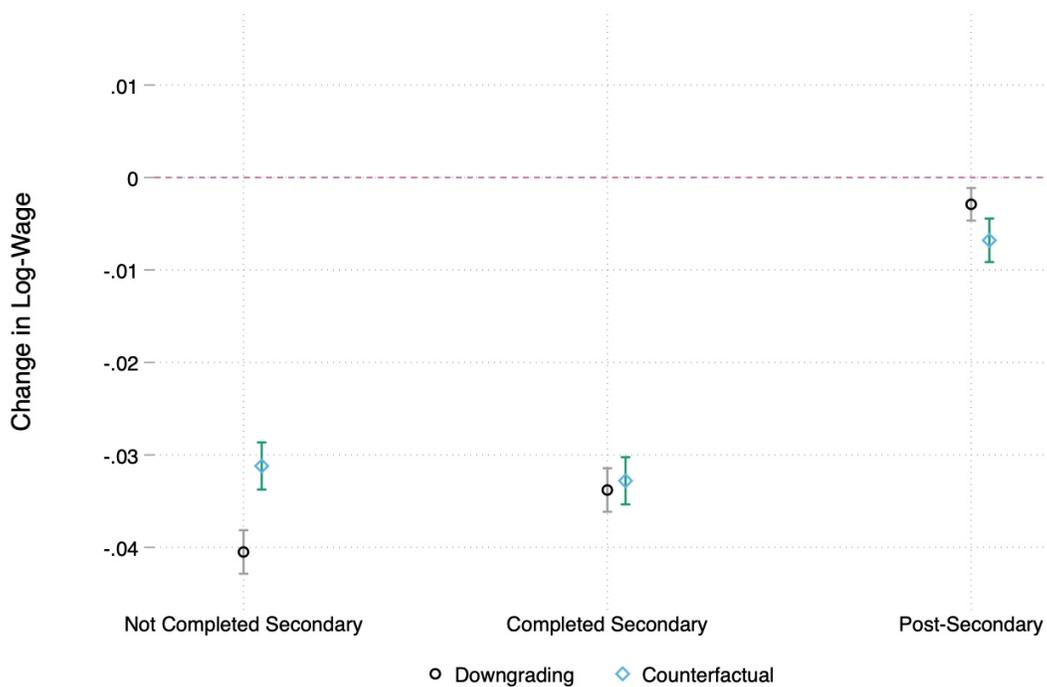


### (b) Full Capital Adjustment
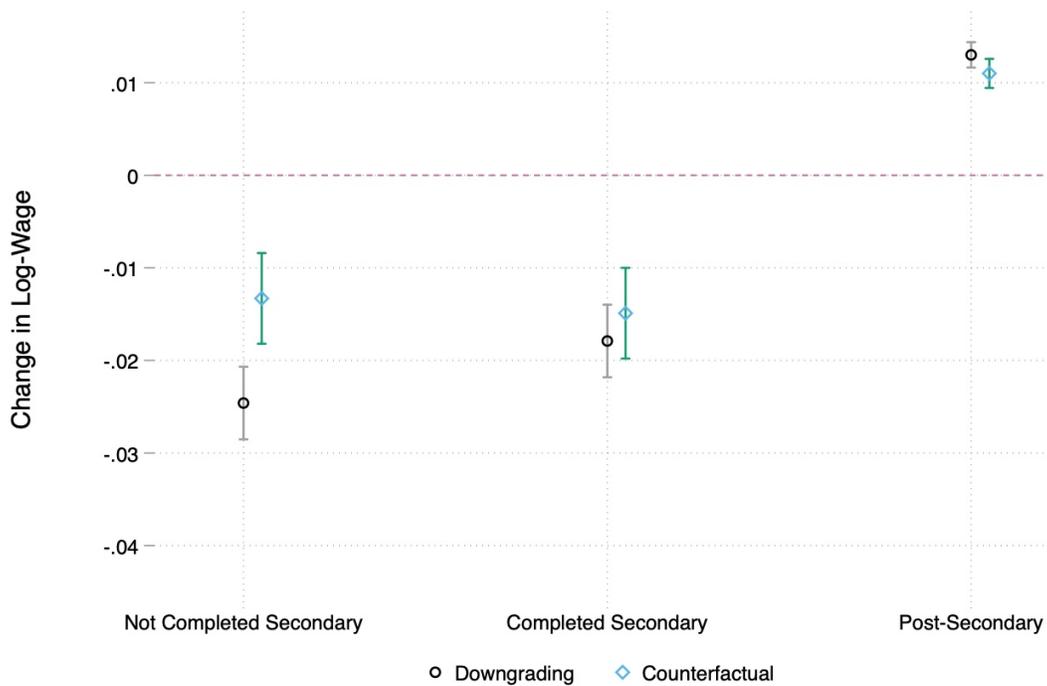


Coefficients from Table 5 are presented with 95% confidence intervals. In Panel A, capital is held fixed. In Panel B, capital is allowed to grow at the same rate as effective labor supply.

Table A6: Total Effect of Immigration on Migrant Wages

| | $\Delta ln(W_{en})$ Under Downgrading | $\Delta ln(W_{en})$ Under No Downgrading | Difference |
|---|---|---|---|
| **Panel A: Fixed Capital** | | | |
| Less than Secondary | -24.78 ( 3.89) | -21.25 ( 3.41) | 3.52 ( 0.49) |
| Completed Secondary | -26.81 ( 3.13) | -28.85 ( 3.41) | -2.04 ( 0.29) |
| Post-Secondary | -40.73 ( 8.70) | -45.97 ( 9.74) | -5.24 ( 1.04) |
| **Panel B: Flexible Capital** | | | |
| Less than Secondary | -23.19 ( 3.87) | -19.46 ( 3.40) | 3.72 ( 0.48) |
| Completed Secondary | -25.22 ( 3.11) | -27.06 ( 3.39) | -1.84 ( 0.29) |
| Post-Secondary | -39.13 ( 8.60) | -44.18 ( 9.62) | -5.04 ( 1.02) |

Percent change in migrant wages due to migration from Venezuela between 2014-2019. In Column 1, migrants are assigned to education groups according to native education shares in their occupation (as in the estimation). In Column 2, migrants are assigned to their observed education (the counterfactual). In Panel B, capital is adjusted proportionally to the increase in effective labor supply. In parenthesis are the standard deviation of 1,000 simulations, with parameters drawn from a joint normal distribution using estimated means and standard errors.

# A2 Comparing Education in Colombia and Venezuela

In this section, I assess the comparability of the Venezuelan and Colombian education systems to demonstrate that, if anything, secondary and post-secondary education is more valuable in Venezuela, in which case I am underestimating the distributional benefits of undoing downgrading (this is demonstrated in Section A6.) First, I look at the 2009 Programme for International Student Assessment (PISA), which included the Venezuelan state of Miranda (which contains around 10% of the Venezuelan population) and is the most recent internationally comparable evaluation of Venezuela's education system. PISA evaluates 15-year-olds' knowledge and skills in reading, math, and science literacy, presenting an opportunity to compare the quality of secondary education five years before the migration wave. Table A7 shows that, out of 74 countries, Venezuela ranks similarly and slightly higher than Colombia in every category (Walker, 2011).

Table A7: Colombian and Venezuela 2009 PISA Score

|  | Colombia | | | Venezuela | | | Sample Range |
|---|---|---|---|---|---|---|---|
|  | Mean | (SD) | Rank | Mean | (SD) | Rank |  |
| Reading Literacy | 413 | (3.7) | 56th | 422 | (5.3) | 52nd | 314-556 |
| Math Literacy | 381 | (3.2) | 64th | 397 | (4.3) | 60th | 331-600 |
| Science Literacy | 402 | (3.6) | 60th | 422 | (4.9) | 53rd | 314-556 |

Results from PISA 2009+. Source: Walker (2011).

I next study the education wage premia for people educated under each system. This should be done in a common labor market, where Colombians and Venezuelans are either fully assimilated into the labor market or face similar barriers to entry. I am unable to do this by comparing previously arrived Venezuelans with native Colombians in Colombia, because the data do not allow me to see when they entered the country and thus to infer whether they were educated in Venezuela or Colombia. I thus look at a different labor market: the United States in 2015 census (IPUMS, 2019). This includes a sizeable population of migrants from each country alongside information on earnings and year of arrival.[29] I restrict the sample to working-age migrants who were born in Colombia or Venezuela and who migrated before 2010 but after completing education (after age 18, or after age 21 for migrants with any post-secondary education).

In Table A8, I regress log income on gender, age dummies (grouped into 10-year bins), and years since arrival (grouped into less than 1 year, 1-4 years, 5-9 years and greater than 10 years) for migrants from each country. The results show similar income premia for each education group: the premia for completed secondary relative to less than completed secondary are insignificant and around 10% for each group, and the premia for post-secondary are 52% for Colombians and 66% for Venezuelans. Venezuelan education is in fact slightly more valuable in the U.S. labor market, though the difference is not statistically significant.

These premia are difficult to interpret if the selection of migrants to the U.S. is not comparable across countries. Table A9 shows that the demographic characteristics and employment rates are similar for Venezuelan and Colombian migrants in the U.S., though Venezuelans are slightly more likely to be male, younger, and arrived more recently, and these characteristics are controlled for in the regression. Most

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[29]Another candidate is the 2010 Panama census, but the 10% subsample only includes 209 working Venezuelans, and almost all have a college degree, which is not true for Colombian migrants in Panama.

Table A8: Migrant Education Earnings Premia in the U.S. in 2015

|  | Colombian-Born | | Venezuelan-Born | |
|---|---|---|---|---|
|  | (1) | (2) | (3) | (4) |
|  | **Ln(Income)** | | | |
| Not Completed Secondary | (excluded) | (excluded) | (excluded) | (excluded) |
| Completed Secondary | 0.06 | 0.10 | 0.06 | 0.09 |
|  | (0.08) | (0.07) | (0.24) | (0.19) |
| Any Post-Secondary | 0.47*** | 0.52*** | 0.68*** | 0.66*** |
|  | (0.07) | (0.07) | (0.22) | (0.17) |
| N | 1,791 | 2,477 | 628 | 846 |
| Individual Controls |  | X |  | X |

Sample restricted to migrants age 15-64, who have been in the U.S. for at least 5 years and who migrated after age 18 or after age 21 if they have any post-secondary. Controls include gender, age group (in 10-year bins), and years since arrival (bins: <1, 1-4, 5-9, ≥10 years). Population weights applied. Robust standard errors in parenthesis. Source: 2015 U.S. Census 1% subsample (IPUMS)

importantly, Venezuelans are more likely to have post-secondary education than Colombians, and this could indicate that they are differently selected on ability. To characterize selection from the home country, it is necessary to use information on the population by education group back home. I do this using the 2005 Colombian and 2001 Venezuelan censuses. First, I note that, according to these censuses, the demographics and education rates of each country looked very similar.[30] In Table A10, I look at the 2015 U.S. working-age migrant population as a share of the home country working-age population in the 2005 and 2001 censuses.[31] This shows that around 2% of working-age Colombians and 1.4% of working-age Venezuelans are in the U.S. Under a simple model of migrant selection, lower migration rates indicate higher costs or barriers to migration, and thus greater selection on ability. The bias that I am concerned about is, precisely, the selection of educated Venezuelans relative to that of Colombians, *relative* to those without completed secondary. What the remaining columns of Table A10 indicate is that, relative to Colombians, Venezuelans are less selected for post-secondary than they are for lower education groups - the ratio of the Colombian to the Venezuelan migrant share of the population is 2 for people without and with completed secondary, but only 1.2 for people with post-secondary. Thus, we may expect that the ability of Venezuelans with less education in the U.S. is more positively selected than that of Colombians, and this would bias down the estimated wage premium for post-secondary educated Venezuelans relative to Colombians.

It is also useful to see how these premia vary by birth cohort, given that Venezuelan migrants in Colombia are younger than those in the U.S. (with an average age of 32 in Colombia in 2019, relative to 47 in the U.S. in 2015). In Table A11, I show that the larger college premium for Venezuelans is concentrated

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[30]Working-age Colombians and Venezuelans were, respectively, %48.1% and 49.0% male, 43.5% and 47.1% under-30, 84.7% and 87.3% under-50, 20.4% and 16.6% with completed secondary education, and 17.7% and 18.7% with post-secondary education.

[31]Though this population could be calculated for more recent years using Colombian labor force data, no such data exists in Venezuela. The 2001 census is the most recent data that allow a count of the population by age and education group in Venezuela.

among migrants under age 45 in 2015, and who thus completed college around 1990 or later. Thus, the returns to post-secondary appear largest for the younger workers, who are more comparable with the recent Venezuelan migrant population in Colombia.

### Table A9: Migrant Characteristics in the U.S. in 2015

|  | Colombian-Born | Venezuelan-Born |
|---|---|---|
| Male (%) | 40.8 | 45.6 |
| Age (mean) | 48.5 | 46.9 |
| Years in Country (mean) | 17.9 | 15.6 |
| Completed Secondary (%) | 30.9 | 19.2 |
| Any Post-Secondary (%) | 58.2 | 75.8 |
| Employment Rate (%) | 78.1 | 75.0 |
| N | 2,477 | 846 |

See notes to Table A8.

### Table A10: Percent of Working-Age Population in Home Country

|  | Colombian Share | Venezuelan Share | Ratio of Colombian to Venezuelan Share |
|---|---|---|---|
| All Working-Age | 2.0 | 1.4 | 1.4 |
| Not Completed Secondary | 0.4 | 0.2 | 2.0 |
| Completed Secondary | 2.6 | 1.4 | 1.9 |
| Any Post-Secondary | 6.9 | 5.6 | 1.2 |

Working-age migrant sample in the 2015 U.S. census is taken as a share of the working-age population in the origin country according to Venezuelan 2001 and Colombian 2005 censuses.

### Table A11: Earnings Premia by Birth Cohort

|  | Colombian-Born | | Venezuelan-Born | |
|---|---|---|---|---|
|  | Age 15-44 | Age 45-64 | Age 15-44 | Age 45-64 |
|  | (1) | (2) | (3) | (4) |
|  | **Ln(Income)** | | | |
| Not Completed Secondary | (excluded) | (excluded) | (excluded) | (excluded) |
| Completed Secondary | -0.16 | 0.19** | 0.14 | 0.02 |
|  | (0.15) | (0.08) | (0.34) | (0.20) |
| Any Post-Secondary | 0.36** | 0.57*** | 0.81** | 0.49*** |
|  | (0.15) | (0.08) | (0.33) | (0.17) |
| N | 611 | 1,180 | 266 | 362 |
| Individual Controls | X | X | X | X |

See notes to Table A8.

# A3 Instrumental Variable Strategy

Equation (8) is biased if migrant labor supply $L_{m,ect}$ is correlated with the error term. Specifically, the concern regards migrant sorting into locations according to the migrant-native wage ratio, as opposed to the traditional concern of sorting according to native wages. To deal with this potential endogeneity, I construct the following instrument for $\ln\left(\frac{L_m}{L_n}\right)_{ect}$:

$$Z_{ect} = \ln\left(\frac{L_{Ven}}{L_{Col}}\right)_{e,c,2005} * \ln\left(\frac{L_m}{L_n}\right)_{e,Nat^{-c},t} \tag{A1}$$

The first term is the log ratio of Venezuelan-born to Colombian-born in the complete 2005 census in education group $e$ and metro area $c$. The second term is the national-level log ratio of migrants to natives in education group $e$ and year $t$, excluding migration into metro area $c$ to reduce the impact of large inflows into cities that are correlated with changes in economic outcomes in those cities (Card, 2001; Tabellini, 2020). This instrument is the standard "shift-share" instrument based on historical migrant populations, adjusted to match the functional form of the endogenous covariate.[32] I use education-specific migrant shares to generate independent variation in predicted labor ratios by education group, exploiting the fact that migrants are more likely to have networks with migrants of similar socioeconomic backgrounds. The first-stage estimates are presented in Figure A5.

The national change in migration in year $t$ is assumed to be exogenous, driven primarily by push factors in Venezuela that are uncorrelated with any economic or other changes occurring in Colombia, reflecting the fact that Venezuelans were primarily migrating to escape poverty and violence in Venezuela. Of greater concern is the potential endogeneity of the 2005 migrant-native ratio, which could be correlated with *changes* in economic outcomes between 2014-2019. This concern is mitigated by the fact that historical migrant shares were determined two decades before the onset of the Venezuelan exodus, well before the election of Hugo Chávez.[33] The instrument would also be invalid if migration before 2005 stimulated dynamic economic responses or subsequent migration correlated with current economic trends (Jaeger *et al.*, 2018). However, there was almost no migration into Colombia between 2005-2015, and the 2005 Venezuelan share was very small relative to the current immigration: in no metropolitan area in 2005 was this share greater than 1%.

It remains possible that migrants historically sorted into locations that had different economic trends unrelated to the current migration. While this cannot be formally tested, I conduct various checks and robustness tests recommended by the literature (Goldsmith-Pinkham *et al.*, 2020). First, I check for a correlation between the 2005 shares and pre-period economic outcomes. Table A12 shows a regression of the 2005 Venezuelan-Colombian log-ratio by education on a set of pre-period metro characteristics. The coefficients are mostly small and insignificant. A 1% increase in 2014 wages is associated with a .012 SD

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[32]By matching the functional form of the endogenous variable, the log transformation gives me substantially more power in the first stage regression, but it is not necessary to replicate my primary results. I also add one to the 2005 Venezuelan population to make the log ratio non-missing in places with no Venezuelans in 2005, and I normalize the 2005 log share to be positive by adding it to its minimum value.

[33]Colombian census data were provided by DANE. While I use the 2005 census to construct the instrument, results using the 1993 census are very similar. There was little subsequent immigration over this period and the correlation between the migrant share in these years is .89. I choose to use the 2005 census because I have access to the complete census, which helps to minimize measurement error, and to mitigate concerns regarding changing municipal boundaries before 2005.

decrease in the 2005 log ratio among workers with post-secondary, and the magnitudes are smaller for other education groups. Most notably, a 1% increase in the unemployment rate is associated with a .06SD decrease in the 2005 log-ratio for workers with completed secondary or post-secondary. However, no coefficient is significant at the 10% level after accounting for multiple hypothesis testing using sharpened false discovery rate q-values with 15 tests (Anderson, 2008).

I next test if historical migrant shares are correlated with pre-trends in wages leading up to the migration. While there are not enough migrants before 2015 to estimate pre-trends in the migrant-native wage ratio, I estimate pre-trends in native wages with the following event-study model:

$$W_{ect} = \sum_{\substack{y=2010,\ldots,2019 \\ y \neq 2015}} [\sigma_{ey} \ln \left( \frac{L_{Ven}}{L_{Col}} \right)_{e,c,2005} * (t = y)] + \gamma_{ec} + \delta_{et} + \epsilon_{ect} \tag{A2}$$

where $\sigma_{ey}$ measures the effect of the 2005 Venezuelan-Colombian log-ratio in education group $e$ in each year relative to the excluded year of 2015. This is presented in Figure A6 with heteroscedasticity-robust 95% confidence interval. Within each education group, native hourly wages do not exhibit a pre-trend associated with the 2005 log ratio. In education group 2, there is a negative pre-trend before 2013, but this leveled out in the 2 years before 2015. Only after 2015 is the 2005 log ratio associated with a wage decline for less-educated natives, consistent with the estimated effect on native wages.

The 2SLS results are presented in Figure A13. The first-stage Kleibergen-Paap Wald statistic (averaged over the 100 migrant random assignments) remains over 50 for each education group, and the coefficients from the first-stage regression are all positive and significant.[34] The parameter estimates estimated via 2SLS are almost identical to those estimated via OLS. This mitigates any concern that migrants are sorting geographically according to the migrant-native wage ratio. Estimating total wage effects and counterfactual wage effects using these estimates generates results very similar to those presented in Section 6.

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[34]The Kleibergen-Paap LM test with a single endogenous regressor is a first-stage F-statistic that is heteroskedasticity robust. I drop the small share of resamples in which the first-stage Kleibergen-Paap Wald statistic is weak.
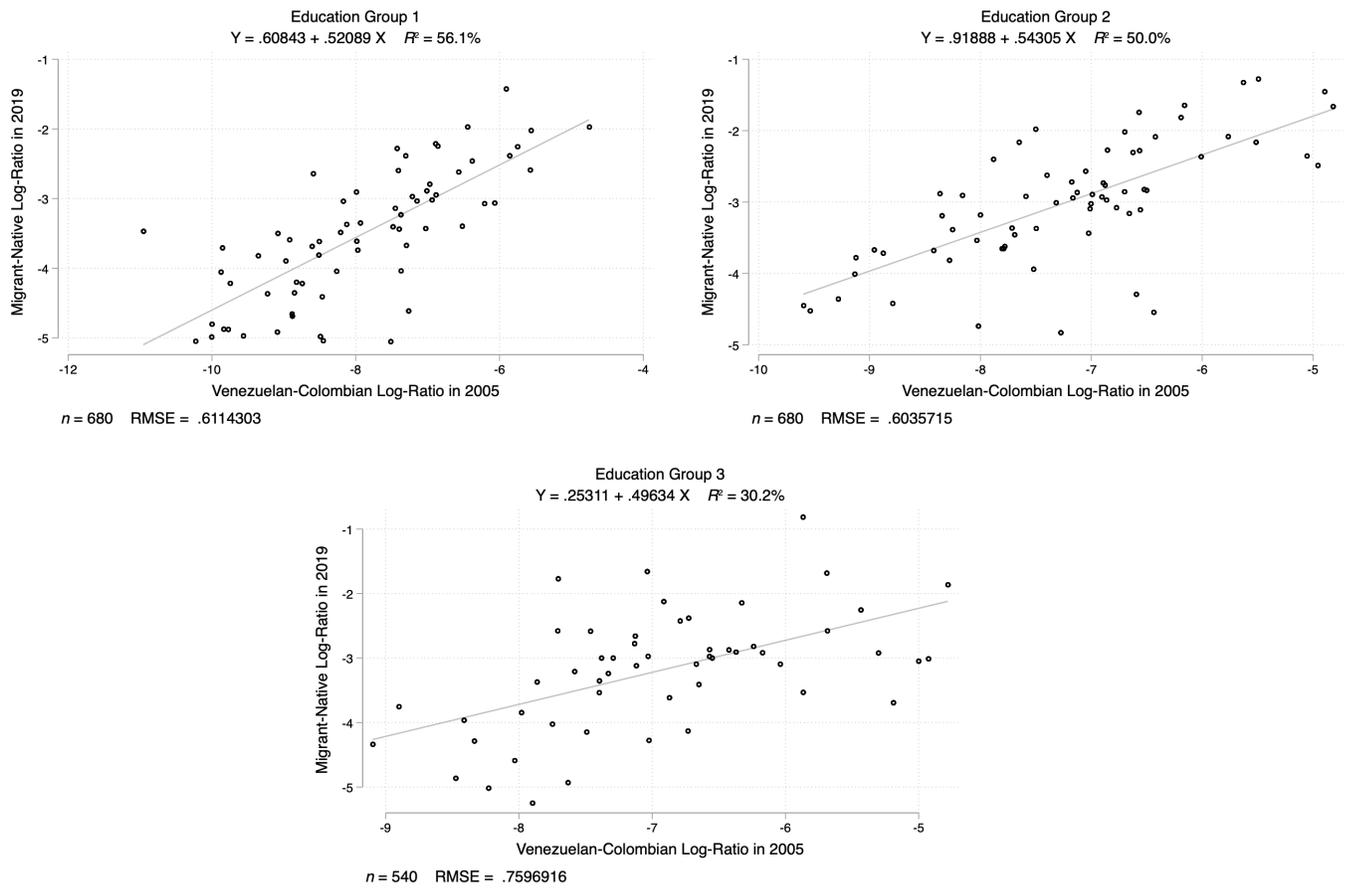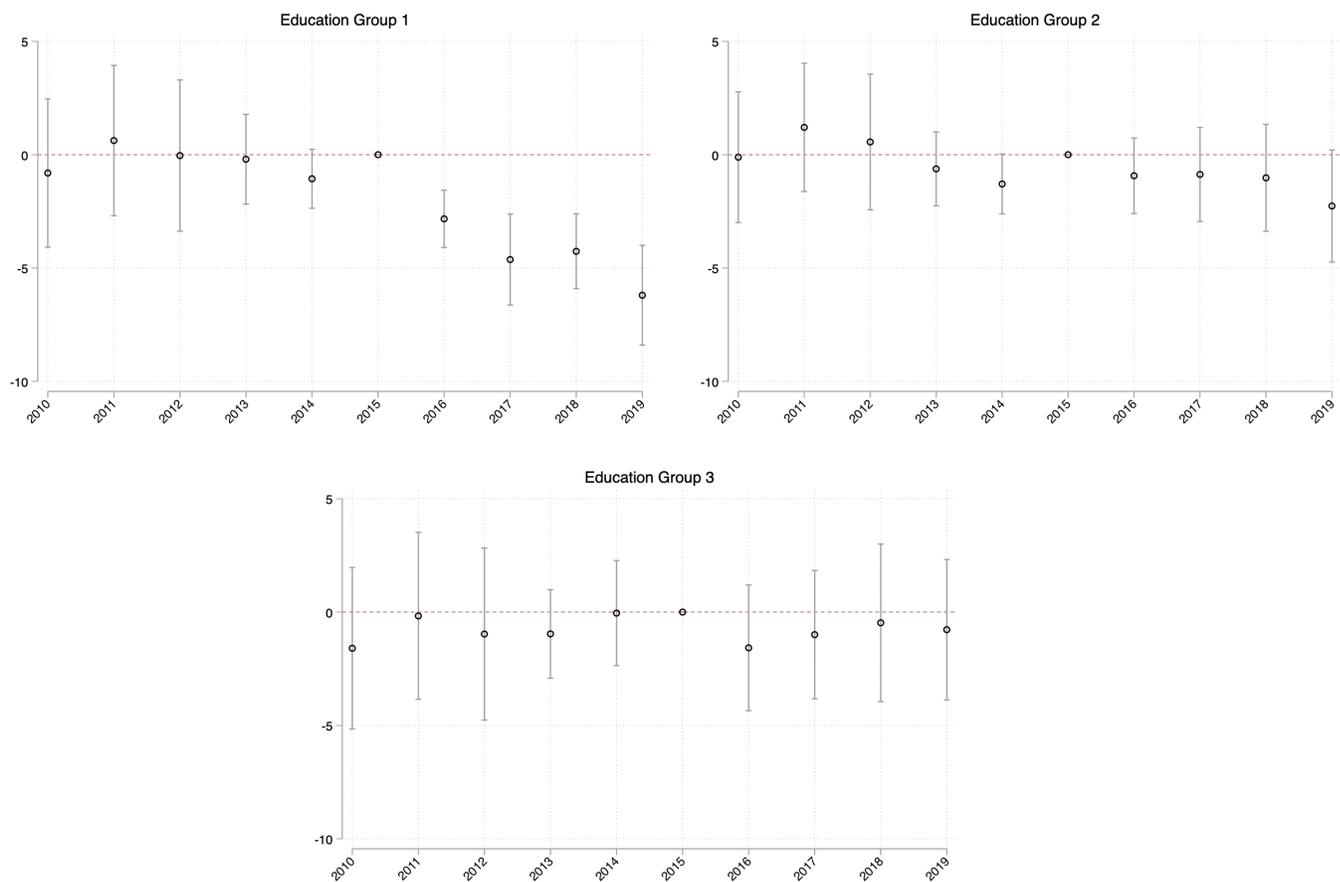
Figure A5: First Stage Regression

# Figure A6: Pre-Trends for Native Log-Wages



Equation (A2) is estimated using native log wages multiplied by 100 and weighted by working population. The log 2005 migrant-native ratio is normalized to a standard deviation of 1. Cluster-robust 95% CIs presented.

## Table A12: Pre-Period Correlates of 2005 Venezuelan-Colombian Log-Ratio

| 2005 Venezuelan-Colombian Log-Ratio: | (1) < Completed Secondary | (2) Completed Secondary | (3) > Completed Secondary |
|---|---|---|---|
| **2014 Metro Characteristic:** | | | |
| Population (100,000) | 0.001 | 0.003 | 0.005 |
| | ( 0.004) | ( 0.004) | ( 0.004) |
| 100*Ln(Hrly Wage) | -0.001 | -0.008 | -0.012** |
| | ( 0.006) | ( 0.005) | ( 0.005) |
| 100*Ln(Hrs per Week) | 0.021* | 0.022* | 0.015 |
| | ( 0.010) | ( 0.011) | ( 0.012) |
| 100*Unemployment Rate | -0.038 | -0.061* | -0.059** |
| | ( 0.035) | ( 0.033) | ( 0.029) |
| 100*LFP Rate | 0.015 | -0.020 | -0.025 |
| | ( 0.019) | ( 0.021) | ( 0.019) |
| N | 79 | 79 | 79 |
| $R^2$ | .051 | .16 | .22 |

2005 log-ratio of the Venezuelan-born to Colombian-born population calculated by education group from the complete 2005 census and normalized to a standard deviation of 1. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

## Table A13: 2SLS Substitutability Parameter Estimates

| | $-\frac{1}{\sigma_{1m}}$ | $-\frac{1}{\sigma_{2m}}$ | $-\frac{1}{\sigma_{3m}}$ |
|---|---|---|---|
| Parameter Estimates: | -0.066 | -0.077 | -0.155 |
| | ( 0.009) | ( 0.009) | ( 0.036) |

| | $\sigma_{1m}$ | $\sigma_{2m}$ | $\sigma_{3m}$ |
|---|---|---|---|
| Parameter Estimates: | 15.13 | 13.04 | 6.45 |
| | ( 2.01) | ( 1.54) | ( 1.48) |

| | | | |
|---|---|---|---|
| Mean K-P Wald Stat. | 59.9 | 71.3 | 91.7 |
| Mean First-Stage Coef. | 0.33 | 0.37 | 0.40 |
| | ( 0.03) | ( 0.03) | ( 0.03) |

Means presented from estimation of (8) under 100 random assignments of migrants to education groups. The instrument is the log migrant-native ratio of the metro area in the 2005 census. Metro-clustered bootstrapped standard errors with 100 resamples in parenthesis. Standard errors for the inverted coefficients are calculated using the Delta method. Kleibergen-Paap Wald statatic is clustered at the metro level.

# A4    Adding Age and Gender to the Nesting Structure

In this section, I adapt the model to separately incorporate age and gender into the nesting structure. To mitigate small sample concerns, I apply the additional nest one at a time and in each case divide the sample into two groups: male-female and over-under 30. I insert this nest between the education and nativity nests, and the new production function is characterized by the following set of equations:

$$Y = AK^{1-\zeta}L^{\zeta} \tag{A3}$$

$$L = \left( \alpha_3 L_3^{\frac{\sigma_3-1}{\sigma_3}} + \alpha_{-3} L_{-3}^{\frac{\sigma_3-1}{\sigma_3}} \right)^{\frac{\sigma_3}{\sigma_3-1}} \tag{A4}$$

$$L_{-3} = \left( \alpha_2 L_2^{\frac{\sigma_2-1}{\sigma_2}} + \alpha_1 L_1^{\frac{\sigma_2-1}{\sigma_2}} \right)^{\frac{\sigma_2}{\sigma_2-1}} \tag{A5}$$

$$L_e = \left( \alpha_{eD1} L_{eD1}^{\frac{\sigma_d-1}{\sigma_d}} + \alpha_{eD2} L_{eD2}^{\frac{\sigma_d-1}{\sigma_d}} \right)^{\frac{\sigma_d}{\sigma_d-1}} \tag{A6}$$

$$L_{ed} = \left( \alpha_{edm} L_{edm}^{\frac{\sigma_{edm}-1}{\sigma_{edm}}} + \alpha_{edn} L_{edn}^{\frac{\sigma_{edm}-1}{\sigma_{edm}}} \right)^{\frac{\sigma_{edm}}{\sigma_{edm}-1}} \tag{A7}$$

where $d\epsilon\{D1, D2\}$ notates the demographic group (either age or gender). The new equation in the system is equation (A6). The elasticity of substitution between demographic groups, $\sigma_d$, is constant across education groups to increase precision. However, I allow the migrant-native substitutability parameter, $\sigma_{edm}$, to vary by both education and age group. In this system, log-wages for $e \in \{1, 2\}$ are:

$$\ln W_{edj} = \ln\left( AK^{1-\zeta}\zeta \right) + \ln\alpha_{-3} + \ln\alpha_e + \ln\alpha_{ed} + \ln\alpha_{edj} + \left( \zeta - 1 + \frac{1}{\sigma_3} \right)\ln L$$
$$+ \left( \frac{1}{\sigma_2} - \frac{1}{\sigma_3} \right)\ln L_{-3} + \left( \frac{1}{\sigma_d} - \frac{1}{\sigma_2} \right)\ln L_e + \left( \frac{1}{\sigma_{edm}} - \frac{1}{\sigma_d} \right)\ln L_{ed} - \frac{1}{\sigma_{edm}}\ln L_{edj} \tag{A8}$$

and for $e = 3$ are:

$$\ln W_{3dj} = \ln\left( AK^{1-\zeta}\zeta \right) + \ln\alpha_3 + \ln\alpha_{3d} + \ln\alpha_{3dj} + \left( \zeta - 1 + \frac{1}{\sigma_3} \right)\ln L$$
$$+ \left( \frac{1}{\sigma_d} - \frac{1}{\sigma_3} \right)\ln L_3 + \left( \frac{1}{\sigma_{3dm}} - \frac{1}{\sigma_d} \right)\ln L_{3d} - \frac{1}{\sigma_{3dm}}\ln L_{3dj} \tag{A9}$$

The estimation of the migrant-native substitutability parameters is analogous to equation (8):

$$\ln\left( \frac{W_m}{W_n} \right)_{edct} = \lambda_{edc} - \frac{1}{\sigma_{edm}}\ln\left( \frac{L_m}{L_n} \right)_{edct} + \epsilon_{edct} \tag{A10}$$

where both the wage ratio and labor ratio now vary by demographic group as well, and education-age-metro fixed effects are included to capture all fixed wage differences across demographic groups within each metro area. As before, these fixed effects are used to back out the productivity parameters, $\alpha_{edj}$. Finally, analogous estimating equations are derived for the substitutability parameters higher up in the nesting structure:

$$\ln\left(\frac{W_{D2}}{W_{D1}}\right)_{ect} = \lambda_{1,ec} + \lambda_{1,et} - \frac{1}{\sigma_d}\ln\left(\frac{L_{D2}}{L_{D1}}\right)_{ect} + \epsilon_{1,ect} \tag{A11}$$

$$\ln\left(\frac{W_2}{W_1}\right)_{ct} = \lambda_{2,c} + \lambda_{2,t} - \frac{1}{\sigma_2}\ln\left(\frac{L_2}{L_1}\right)_{ct} + \epsilon_{2,ct} \tag{A12}$$

$$\ln\left(\frac{W_3}{W_{-3}}\right)_{ct} = \lambda_{3,c} + \lambda_{3,t} - \frac{1}{\sigma_3}\ln\left(\frac{L_3}{L_{-3}}\right)_{ct} + \epsilon_{3,ct} \tag{A13}$$

The procedure for estimation is exactly as described in the paper, including the use of the instrument based on education-specific migrant enclaves presented in equation (A1), as well the iterated random assignment of migrants into age- or gender-education groups according to the native distribution in their observed occupation. Thus, I estimate the substitutability between natives in each demographic-education bin and migrants who work in occupations competing with those workers and predict the changes in the total wage effects if migrants instead compete with workers of their own demographic-education group.

The results presented in Table A14 indicate that migrant-native substitutability does not vary by demographic group and is very similar to the values estimated in the initial model without age or gender. $\sigma_3$ and $\sigma_2$ are also close to the values estimated in the initial model. The elasticity of substitution across age groups, $\sigma_d$, is 3.9, indicating imperfect substitutability across groups. This is consistent with the parameter values of around 5 that have been found in the US and the UK, and with Fernández & Messina (2018) in Latin America, which finds elasticities of substitution across experience groups of 3.6-5.5. On the other hand, the inverse elasticity of substitution across genders is positive. This does not have a clear theoretical interpretation (it could be interpreted as "greater than perfect substitutability", or in other words, the relative wage of men increases as the relative supply of men increases). I simply interpret this as perfect substitutability across genders, and I set $\sigma_d$ to 50 when calculating total wage effects under the gender nest. As a result, unlike with age, any differential competition across genders will not affect the gender wage gap.

### Table A14: Substitutability Parameters in Model with Demographic Nest

| | $-\frac{1}{\sigma_{1dm}}$ | $-\frac{1}{\sigma_{2dm}}$ | $-\frac{1}{\sigma_{3dm}}$ | $-\frac{1}{\sigma_{1dm}}$ | $-\frac{1}{\sigma_{2dm}}$ | $-\frac{1}{\sigma_{3dm}}$ | $-\frac{1}{\sigma_d}$ | $-\frac{1}{\sigma_2}$ | $-\frac{1}{\sigma_3}$ |
|---|---|---|---|---|---|---|---|---|---|
| | **Alternate Model 1: Added Age Nest** | | | | | | | | |
| | **Age≤30** | | | **Age>30** | | | | | |
| OLS | -0.07 | -0.07 | -0.13 | -0.07 | -0.07 | -0.14 | -0.26 | -0.33 | -0.72 |
| | ( 0.01) | ( 0.01) | ( 0.03) | ( 0.01) | ( 0.01) | ( 0.04) | ( 0.14) | ( 0.20) | ( 0.41) |
| 2SLS | -0.07 | -0.08 | -0.14 | -0.07 | -0.08 | -0.17 | | | |
| | ( 0.01) | ( 0.01) | ( 0.04) | ( 0.01) | ( 0.01) | ( 0.05) | | | |
| Mean K-P Stat | 55.9 | 62.2 | 83.5 | 58.1 | 71.7 | 95.0 | | | |
| | **Alternate Model 2: Added Gender Nest** | | | | | | | | |
| | **Male** | | | **Female** | | | | | |
| OLS | -0.07 | -0.07 | -0.13 | -0.06 | -0.08 | -0.15 | 0.14 | -0.33 | -0.95 |
| | ( 0.01) | ( 0.01) | ( 0.03) | ( 0.01) | ( 0.01) | ( 0.04) | ( 0.14) | ( 0.23) | ( 0.56) |
| 2SLS | -0.07 | -0.07 | -0.16 | -0.06 | -0.08 | -0.18 | | | |
| | ( 0.01) | ( 0.01) | ( 0.04) | ( 0.01) | ( 0.01) | ( 0.04) | | | |
| Mean K-P Stat | 59.1 | 70.2 | 88.7 | 50.7 | 63.9 | 96.2 | | | |

Means presented from the estimation under 100 random assignments of migrants to demographic groups. Metro-clustered bootstrapped standard errors with 100 resamples in parenthesis.

Table A15 presents the observed changes in labor supply and predicted changes in wages under the scenarios of occupational downgrading (migrants assigned to demographic groups according to their observed occupation, as was done during estimation) and no downgrading (migrants assigned to their actual demographic group). Column 1 shows that migrants disproportionately work in jobs that tend to have more natives under age 30. Workers without completed secondary under age 30 experience a 10% increase in labor supply. Thus, because of imperfect substitutability across age groups, the effects of wage competition in education group 1 are larger for younger workers. Under the counterfactual, migrants are shifted mostly from jobs with older, less-educated workers to jobs with younger, more-educated workers. This interesting pattern highlights that migrant downgrading is mostly increasing competition for older, less-educated natives. Under policies to address downgrading, they are the ones who benefit the most, while younger, better-educated workers face the largest increase in competition and resulting wage drop. Panel B demonstrates that migrants entered occupations that tend to employ slightly more women than men, even though employed migrants are more likely to be male. However, this does not lead to notably different wage effects for women, in part because of high substitutability across genders. In both cases, the average wage effects by education group are comparable to those based on the initial model.

Table A15: Native Wage Effects in Model with Demographic Nest

| | With Downgrading | | Without Downgrading | |
|---|---|---|---|---|
| | %Δ Labor Supply | Predicted %Δ Wage | %Δ Labor Supply | Predicted %Δ Wage |
| **Panel A: Added Age Nest** | | | | |
| **Education Group 1** | | | | |
| Age ≤ 30 | 9.99 | -3.90 | 10.49 | -3.53 |
| Age > 30 | 7.34 | -3.62 | 3.83 | -2.57 |
| Average | 7.90 | -3.68 | 5.24 | -2.78 |
| **Education Group 2** | | | | |
| Age ≤ 30 | 7.01 | -3.04 | 11.71 | -3.42 |
| Age > 30 | 5.60 | -2.84 | 5.93 | -2.70 |
| Average | 6.16 | -2.92 | 8.21 | -2.97 |
| **Education Group 3** | | | | |
| Age ≤ 30 | 5.74 | -0.60 | 9.39 | -1.04 |
| Age > 30 | 2.98 | -0.35 | 3.81 | -0.61 |
| Average | 3.88 | -0.40 | 5.62 | -0.70 |
| **Panel B: Added Gender Nest** | | | | |
| **Education Group 1** | | | | |
| Male | 7.26 | -4.47 | 5.75 | -3.24 |
| Female | 8.93 | -3.95 | 4.42 | -3.34 |
| Average | 7.90 | -4.31 | 5.24 | -3.27 |
| **Education Group 2** | | | | |
| Male | 5.53 | -3.72 | 8.67 | -3.51 |
| Female | 7.03 | -3.31 | 7.57 | -3.46 |
| Average | 6.16 | -3.56 | 8.21 | -3.49 |
| **Education Group 3** | | | | |
| Male | 3.82 | -0.15 | 5.75 | -0.51 |
| Female | 3.93 | -0.13 | 5.49 | -0.54 |
| Average | 3.88 | -0.14 | 5.62 | -0.53 |

Percent change in total labor supply and native wages due to migration from Venezuela between 2014-2019. In Columns 1-2, migrants are assigned to demographic groups according to native distribution in their occupation (as in the estimation). In Columns 3-4, migrants are assigned to their observed demographic group (the counterfactual).

# A5    Generalized Production Function

In this section, I estimate a generalized production function that allows the elasticities of substitution to vary flexibly across all education-nativity groups. With 6 groups (3 education groups and 2 nativity groups), combined with a restriction that the cross-elasticities are symmetric, it is necessary to estimate 15 cross-elasticities. This is more demanding of the data relative to the nested CES model, which only required estimating 5 elasticities. However, it is still possible to estimate and can help to motivate the choice of nesting structure in the nested CES framework. I consider a Generalized Leontief production function, which, similar to a translog production function, can be thought of as a second-order approximation to any arbitrary production function. The advantage of the Generalized Leontief is its empirical tractability since it results in a linear-in-parameters wage equation (Diewert, 1971). Production takes the following form:

$$Y = \sum_j \sum_i \gamma_{ij} \left( L_i L_j \right)^{\frac{1}{2}} \tag{A14}$$

where $\gamma_{ij} = \gamma_{ji}$ by the symmetry of second derivatives. By leaving capital out of the production function, I implicitly assume strong capital separability, motivated by both the difficulty of measuring capital and the short period of migration studied. Under perfect competition, wages equal the marginal product of labor:

$$w_i = \gamma_{ii} + \sum_{i \neq j} \gamma_{ij} \left( \frac{L_j}{L_i} \right)^{\frac{1}{2}} \tag{A15}$$

In this system, a positive (negative) $\gamma_{ij}$ indicates complementarity (substitutability) between factors $i$ and $j$. Following Borjas (1983), I convert these parameters into the Hicks partial elasticity of complementarity, $c_{ij}$, which measures the effect of a relative change in the quantity of $j$ on the price of $i$:

$$c_{ij} = \frac{\gamma_{ij} \bar{w}}{2 w_i w_j \left( P_i P_j \right)^{\frac{1}{2}}} \quad \text{when } i \neq j \tag{A16}$$

where $P_i = \frac{L_i}{\sum_k L_k}$ and $\bar{w} = \sum_k P_k w_k$.

Equation (A15) describes the system of equations that I simultaneously estimate using seemingly unrelated regression, with the constraint that $\gamma_{ij} = \gamma_{ji}$ and including metro fixed effects. Like in the nested-CES estimation, I hold the native population fixed in 2014 and assign migrants to education groups according to their observed occupation. Rather than using an iterated random procedure to assign migrants to education groups, I assign them to the median native education in their occupation, which was found in Table A4 to generate very similar results in the nested-CES framework. I also do not use the instrument for migrant arrival, motivated by the similarity of the OLS and 2SLS estimates in the primary estimation. Without these simplifications, the estimation is severely underpowered.

The resulting cross-group coefficients ($\gamma_{ij}$) and elasticities of complementarity ($c_{ij}$) are presented in Table A16. The elasticity of complementarity in the first column demonstrates that natives in education groups 1-2 are substitutes, though the standard error is imprecise. The second column demonstrates that substitutability across natives in education groups 1-3 and 2-3 are closer to each other and closer to 0. These parameters are not significantly different from each other, and in all cases include values that are both complements and substitutes within their 95% confidence intervals. Nonetheless, they motivate a model in

which workers with and without completed secondary are closer substitutes than workers with and without post-secondary, which is the assumption made in the nested-CES framework.

It is also hard to draw conclusions regarding the substitutability between migrants and natives in the Generalized Leontieff framework due to the large standard errors. However, one result that stands out is that migrants appear to be more substitutable with other migrants than with natives, especially migrants in education groups 2 and 3.

Table A16: Generalized Leontieff Estimation Results

| | Natives E2 | Natives E3 | Migrants E1 | Migrants E2 | Migrants E3 |
|---|---|---|---|---|---|
| **Coefficient Estimates** | | | | | |
| Natives E1 | -1.07 | -0.03 | 0.06 | 0.03 | -0.16 |
| | ( 3.44) | ( 0.29) | ( 0.02) | ( 0.02) | ( 0.06) |
| Natives E2 | | 0.05 | -0.08 | -0.01 | 0.11 |
| | | ( 0.27) | ( 0.02) | ( 0.02) | ( 0.06) |
| Natives E3 | | | 0.03 | -0.01 | 0.09 |
| | | | ( 0.01) | ( 0.01) | ( 0.05) |
| Migrants E1 | | | | 0.08 | -0.16 |
| | | | | ( 0.05) | ( 0.06) |
| Migrants E2 | | | | | -0.31 |
| | | | | | ( 0.08) |
| **Hicksian Elasticity of Complementarity** | | | | | |
| Natives E1 | -2.75 | -0.04 | 0.91 | 0.77 | -3.49 |
| | ( 8.85) | ( 0.38) | ( 0.30) | ( 0.51) | ( 1.31) |
| Natives E2 | | 0.06 | -1.10 | -0.23 | 2.17 |
| | | ( 0.32) | ( 0.27) | ( 0.46) | ( 1.18) |
| Natives E3 | | | 0.21 | -0.12 | 0.90 |
| | | | ( 0.07) | ( 0.12) | ( 0.50) |
| Migrants E1 | | | | 10.90 | -18.62 |
| | | | | ( 6.81) | ( 6.98) |
| Migrants E2 | | | | | -60.56 |
| | | | | | ( 15.63) |

Estimation via Seemingly Unrelated Regression with migrants assigned to the median education group among natives in their occupation between 2010-2015. E1, E2 and E3 refer to less than secondary, completed secondary, and post secondary respectively. Standard errors for the elasticities of complementarity are calculated using the Delta Method.

# A6 Sensitivity Analysis

In this section, I explore the sensitivity of the total wage effect to variation in the across-education substitutability parameters, $\sigma_2$ and $\sigma_3$, and the labor share, $\lambda$, as well as the degree of error in migrant assignment under the "no downgrading" counterfactual.

In Figures A7 and A8 I vary $\sigma_2$ and $\sigma_3$, which were estimated somewhat imprecisely in Table **??**. As $\sigma_2$ increases, the wage effects for workers with and without completed secondary equalize very slowly. However, the sensitivity is small as $\sigma_2$ increases as high as 4.5, and only at the very large value of 15 (not shown) does the gap in effects between these groups begin to close. Wage effects are more sensitive to increases in $\sigma_3$, which shifts negative wage effects of migration from lower to higher education groups, and thus reduces the gains to undoing migrant downgrading for low-education natives. However, the consequences of downgrading persist for workers without completed secondary for values of $\sigma_3$ as high as 2.5, which is higher than values estimated in the U.S. or the U.K. Figure A9 also shows that, as discussed in Section 6, varying the labor share parameter affects all education groups equally because of the skill-neutrality of capital, and within plausible values of .4 to .6 has little consequence for the magnitude of the wage effects.

A remaining concern regards the assumption that migrants and natives have comparable skill within an education group. If this assumption is wrong, for example, if the Venezuelan education system is higher- or lower-quality, and if the goal of the counterfactual reassignment is to match migrants to education groups according to their skill, then the counterfactual effectively matches migrants to the wrong education group. In Figure A10, I explore sensitivity to moving a share of the migrants in each education group in the counterfactual into neighboring groups according to the degree of skill mismatch. For example, when the degree of skill mismatch is .2, 20% of the migrants in education groups 1 and 2 are shifted up to groups 2 and 3 respectively. When it is -.2, 20% of migrants in groups 2 and 3 are shifted down to 1 and 2 respectively. We can see that, even if migrants are under-skilled such that 20% should match to a lower education group, there are still benefits to undoing downgrading for natives without secondary, on the scale of a .5pp gain rather than a 1pp gain. Given the results from Section A2, the more likely scenario is that Venezuelan education is worth slightly *more* than Colombian education, in which case the benefits of undoing downgrading for workers without secondary may be even larger, on the scale of 1.5pp if 20% of migrants are shifted up an education group.

In a related issue, the model assumes that migrants who downgrade are comparable with those who do not. If this is wrong, then a share of the reallocated migrants should instead be placed in a neighboring education group. This is analogous to the previous exercise, except now only migrants who downgraded, as opposed to all migrants, are shifted to a neighboring group according to the degree of skill mismatch. Thus, as shown in Figure A11, counterfactual results are much less sensitive to migrants being placed in the wrong group. In an extreme case in which 30% of downgrading migrants are reallocated to the education group below their observed education, the benefits of undoing downgrading are still .7pp for workers without secondary.

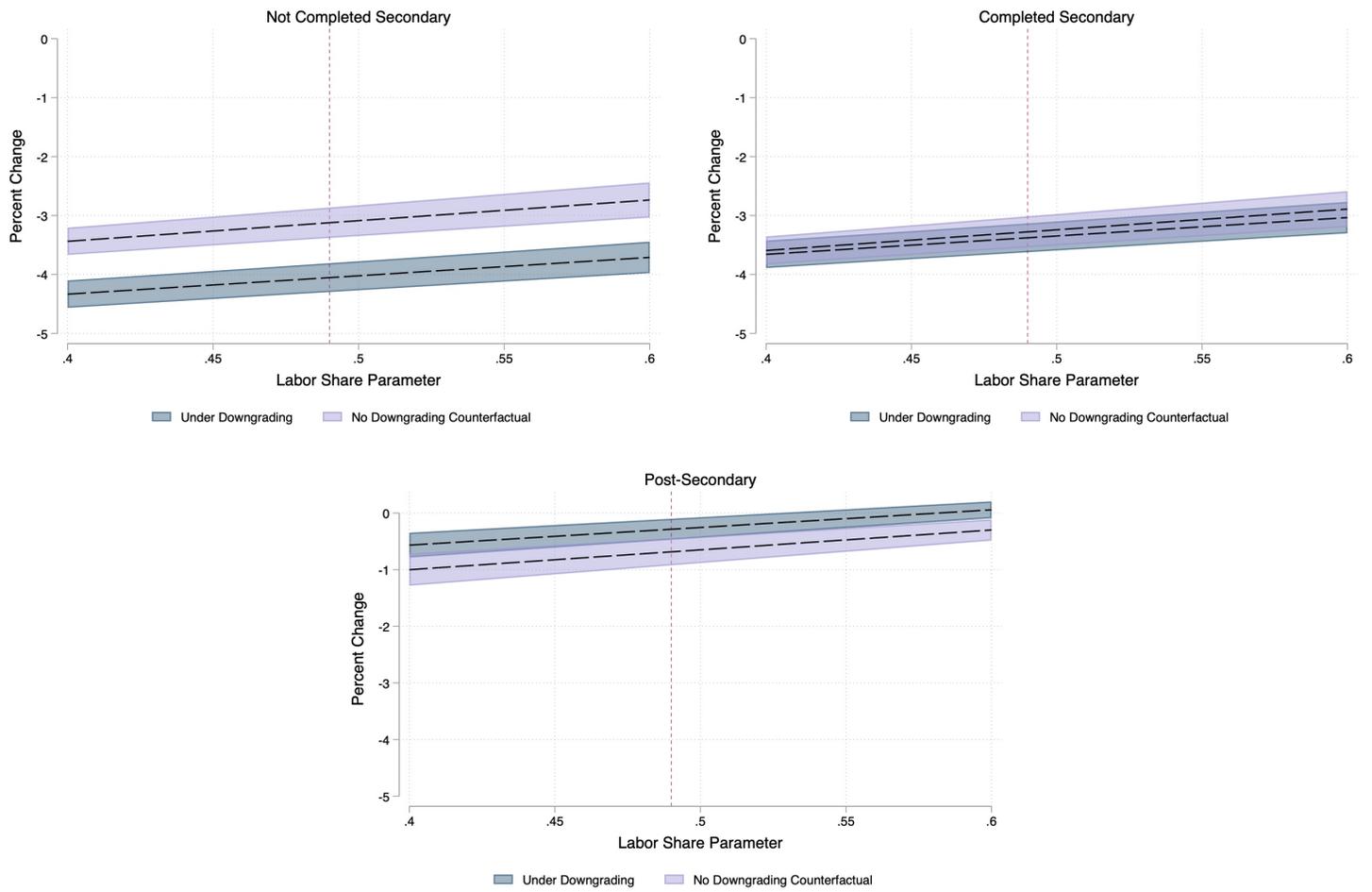## Figure A7: Wage Effect Sensitivity to $\sigma_2$
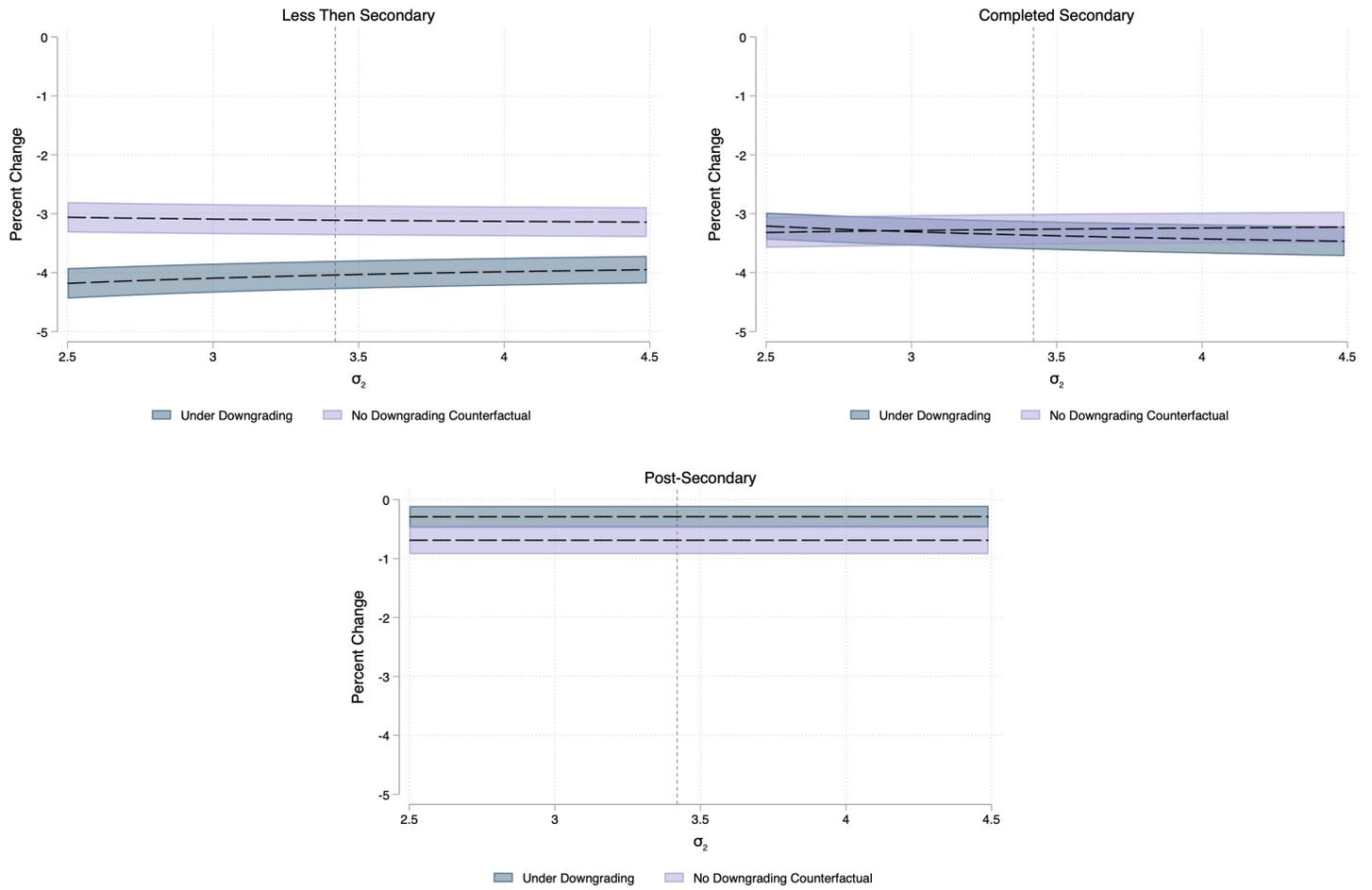


The y-axis measures the effect of migration on native wages between 2014-2019. The red vertical line marks the estimated value of $\sigma_2 = 3.42$. $\sigma_3$ is fixed to the estimated value of 1.15. 95% confidence intervals presented using the standard deviation of the wage effect among 1,000 draws from a joint normal distribution of estimated parameter values.

63

# Figure A8: Wage Effect Sensitivity to $\sigma_3$
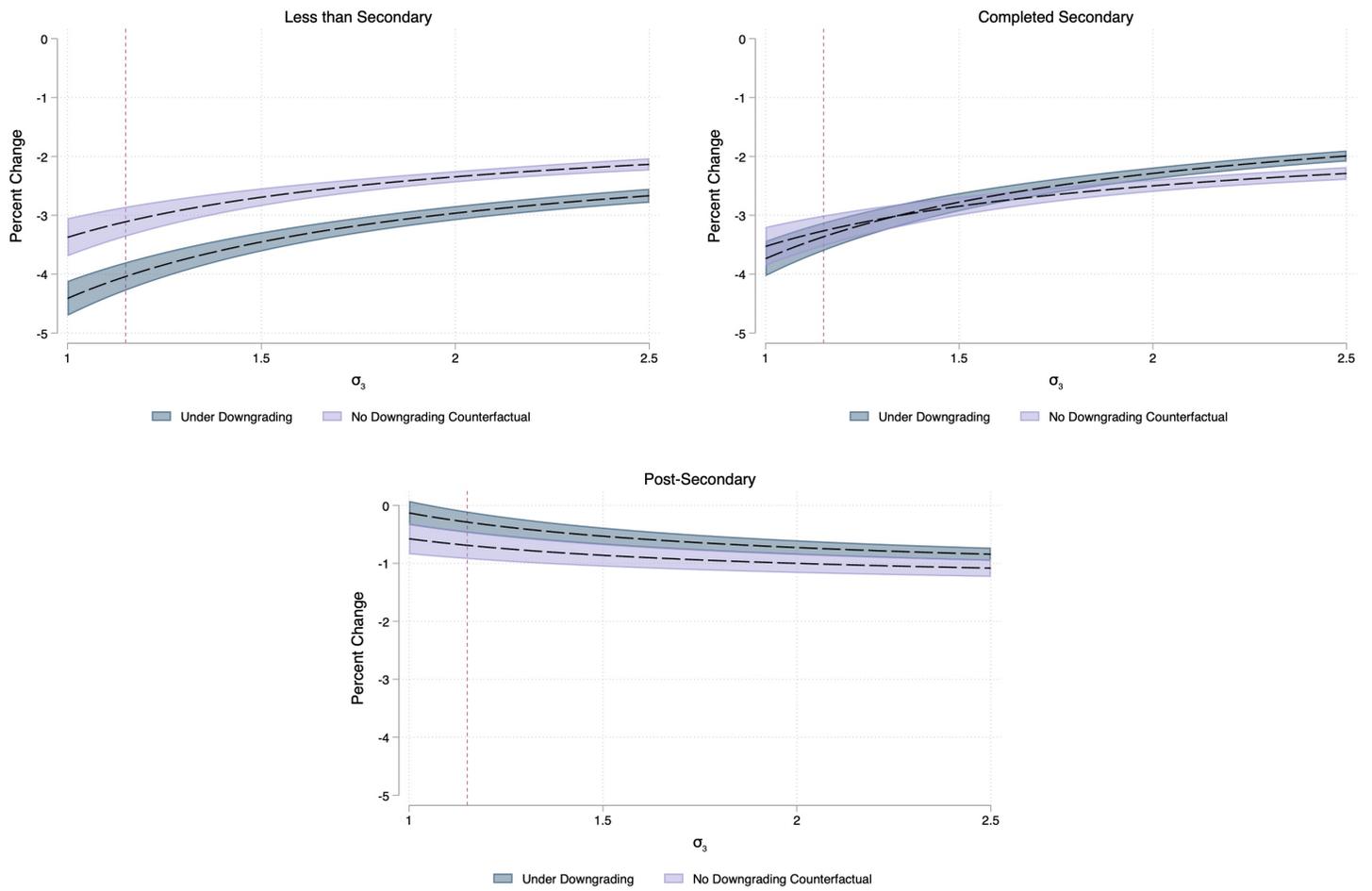


See notes to Figure A7. The red vertical line marks the estimated value of $\sigma_3 = 1.15$. $\sigma_2$ is fixed to the estimated value of 3.42.

Figure A9: Wage Effect Sensitivity to Labor Share ($\lambda$)



See notes to Figure A7. The red vertical line marks the value used in the estimation of $\lambda = .49$.

## Figure A10: Sensitivity to Within-Education Migrant-Native Skill Differences



**Change in Wage Effect Under Counterfactual**
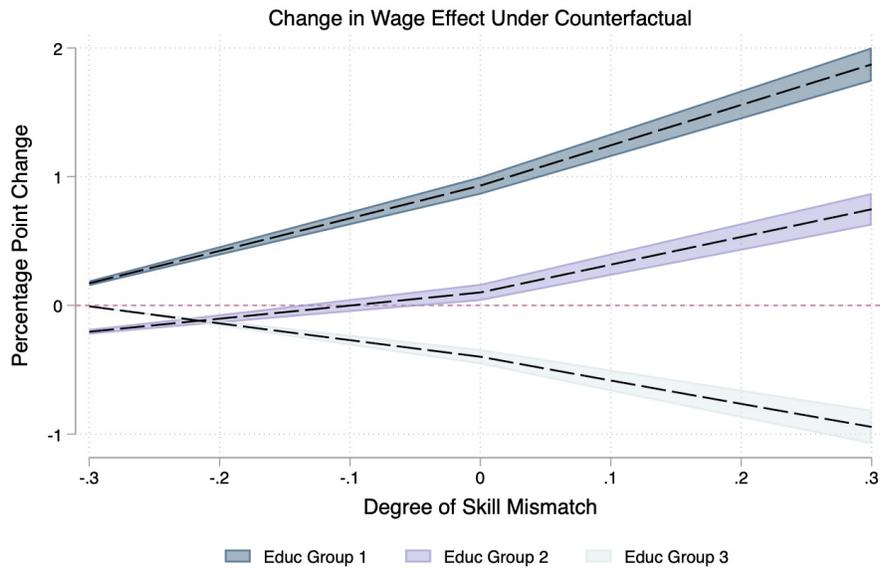
The y-axis measures the *change* in the effect of migration on native wages between 2014-2019 under the no downgrading counterfactual. Degree of skill mismatch indicates share of migrants in each education group shifted up an education group in the counterfactual (1-to-2 and 2-to-3), or if negative, down an education group (3-to-2 and 2-to-1).

## Figure A11: Sensitivity to Skill Differences Only Among Reallocated Migrants



**Change in Wage Effect Under Counterfactual**
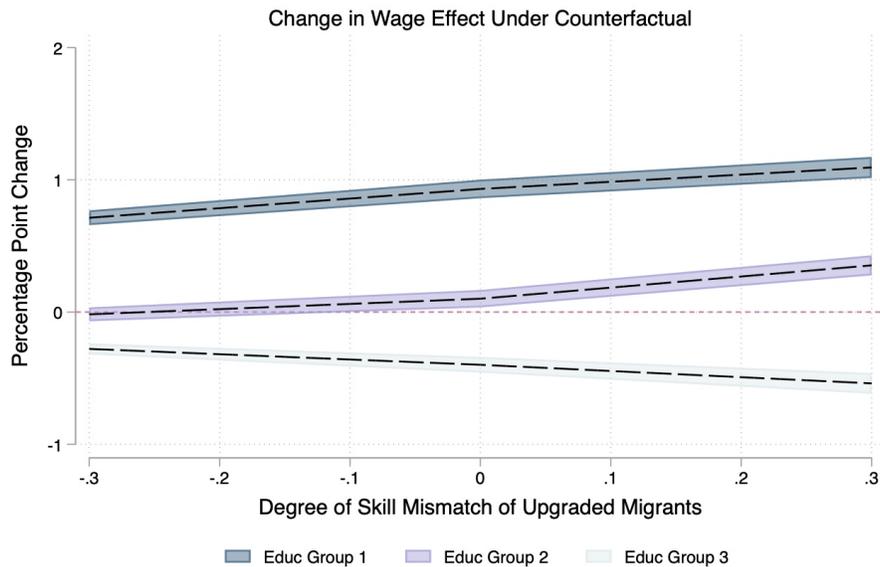
See notes to Figure A10. This time, the degree of skill mismatch indicates share of migrants *among those reallocated in the counterfactual* who are shifted up an additional education group (2-to-3 if reallocated to 2), or if negative, down an education group (3-to-2 if reallocated to 3 and 2-to-1 if reallocated to 2).

66