ABSTRACT
We study the effects of an unexpected and large migration from Venezuela on Peruvian labor markets. From 2017 to 2019, about 800,000 Venezuelans migrated to Peru, with 84% settling in the Lima metropolitan area. The percentage of Venezuelans in the working age population in Lima increased from nearly 0 to over 10%, with migrants having higher education on average than the local labor force. We propose a simple assignment model of the labor market, which suggests that migration will lead to a reallocation of local workers toward low-skilled jobs. Using synthetic control methods and comparing Lima with a group of other Peruvian metropolitan areas, we find evidence of adjustment in occupational structure in the direction predicted by the model with few decreases in employment of local workers.
1 INTRODUCTION

What are the implications of a rapid and unexpected mass migration for labor markets in the host country? Does such migration necessarily provoke large unemployment and drastically falling salaries? Or can labor markets, under some circumstances, adjust to large, unexpected changes in labor supply, reallocating workers, and productive resources without major disruptions? In this paper, we study these questions using the case of recent Venezuelan migration to Peru.

Between 2015 and 2020, over five million people left Venezuela as a result of political, economic, and humanitarian crisis in the country (Chaves-González and Echevarría Estrada 2020). The largest destination countries of Venezuelan migrants were Colombia and Peru. In Peru, in particular, whereas there were only about 60,000 Venezuelans residing in Peru in late 2016, by the end of 2019 there were over 870,000. As a consequence, the number of individuals joining the labor force in Peru approximately doubled in 2018 in relation to recent years (Asencios and Castellares 2020). Moreover, more than 60% of migrants over 15 had more than a high school education, and 30% had completed college, versus 43% and 16% respectively for the local population of Lima and 33% and 13% for Peru. This was, then, a massive, unexpected shock to labor supply, with relatively (in relation to the local population) skilled workers.

We model migration as a shock to the labor force using an assignment model of the labor market, in which workers (both local and migrant) sort into different types of jobs according to the market reward for job-relevant skills, and the market rewards are determined endogenously. Absent price or technological rigidities, an important implication of the model is that migration will lead to a reallocation of at least some of the local labor force toward more elementary jobs.

To test our model and study empirically the consequences of this mass migration, we take advantage that about 84% of all Venezuelan migrants settled in Lima, leading to a large increase in the potential labor force population in Lima and that the migrant inflow to other cities demonstrated smaller increases as a share of city population than migration to Lima. We construct a synthetic control for Lima using monthly data from the period 2013–2019 from Peru’s next largest metropolitan areas and estimate the effects of mass migration on employment, income, hours worked, informal employment and type of occupation. We distinguish the effects by gender, age, and skill level of local workers. As robustness tests, we also consider alternative specifications, alternative definitions of synthetic controls restricting control cities to be south of Lima and consequently farthest away from the main entry point of migrants in the North of Peru as well as restricting synthetic controls to cities where very little Venezuelan migration occurred.

We find little effects on employment, hours worked, and labor income. We find, however, evidence of larger adjustments in the occupational structure, with increases in elementary jobs for local workers. That is, consistent with our model, migrants seem to have shifted local workers at the margin toward jobs in which education skills are less useful. We also find some evidence of lower population growth in Lima versus other metropolitan areas during the period migrants arrive, suggesting possible domestic out migration from Lima in response to the shock. Overall, it is suggestive of absorption of a large shock to the labor supply, consistent with few important binding rigidities in the labor market.

The literature on the economic effects of migration has often relied on what Acemoglu and Autor (2011) calls the “canonical” model of the labor market, in which workers of two or more types, defined by their education or skill, participate in separate markets. Borjas (2003) and Ottaviano and Peri (2012), among others, have proposed general equilibrium models to study the effect of immigration on salaries, distinguishing between different types of labor according to skill levels as factors in a CES aggregate production function; see Lewis (2017) for a perceptive review. In that line Dustmann et al. (2012), estimate a model in which migrants are not preassigned to skill groups, allowing the possibility of “downgrading” of immigrants on arrival.

Unlike previous work, our contribution studies the possibility that local workers may transit at the margin between different job types. In our model, which relates to recent assignment models of

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1 Lima is defined as the metropolitan area of Lima, comprising Lima (the capital city) and the adjacent port of Callao.
the labor market like those of Costinot and Vogel (2010) and the “Ricardian” model of Acemoglu and Autor (2011), the set of skills associated to different jobs may change in response to changing market conditions, affecting the sorting of both local and migrant workers. This is perhaps more of an issue for the Venezuelan migrants in Peru and more generally for South-South migration than for the South-North migration episodes motivating most previous work on migration.

We also contribute to the empirical literature on the labor market effects of mass migration episodes. Interest in studying migration linked to humanitarian disasters was sparked by the Mariel boatlift episode of 1980. Because they are (in principle) sudden, unexpected shocks, migrations linked to humanitarian disasters provide a window to understanding the effects of migration for local workers, and an opportunity to witness the adjustment process in labor markets in reaction to supply shocks. In a seminal contribution, using survey data from a rotating panel, Card (1990) finds no effect of the Mariel boatlift on wages and employment for low-skilled local workers, including previous Cuban migrants. He provides evidence that one adjustment mechanism was the slowing down of migration to Miami from elsewhere within the United States. However, Borjas (2017) re-estimates the impacts of the Mariel boatlift focusing on the subset of high school dropouts, and finds their wage in Miami dropped significantly, by as much as 30 percent.

Recently, Peri and Yasenov (2019) revisit the labor market effects of the Mariel boatlift using synthetic control methods. They also focus particularly on low-skilled workers and find no significant difference in the wages of high-school drop-outs in Miami relative to the synthetic control after 1980, and no consistent evidence of a short-term or long-term decrease in low-skilled labor demand.

Following Peri and Yasenov (2019), we use synthetic control methods to provide inferences about the effect of a mass migration episode. The Venezuelan migration episode we study is somewhat different. First, it was a somewhat larger shock (a 10% increase in the labor force in the main city in the country, rather than a 7% increase in one city linked to a much larger labor market.) And second, the migrant population was relatively educated in comparison with the local labor force, unlike the case of the Mariel boatlift.

Among related work, Santamaria (2020) studies the impact of Venezuelan migration to Colombia using difference in difference methods and identifies the location of migrants by using geographical variation in the Internet search intensity of keywords that Venezuelans are more likely to use compared to Colombians. She finds a mild reduction in wages and null effects on employment. Bahar et al. (2020) use administrative data related to a migratory amnesty program offered by the Colombian government to track their location and estimate negative but negligible effects of on the formal employment of Colombian workers. Lebow (2020) uses geographic variation in exposure to migration combined with an instrumental variable strategy based on the historical settlement patterns of Venezuelans to show that the Venezuelan exodus in Colombia caused a large decrease in real hourly wages for local workers in low-skill occupations, but almost no effect on employment and little occupational upgrading by locals.

There are several previous studies on the labor market effects of Venezuelan migration to Peru. Asencios and Renzo Castellares (2020) study the changes in relative employment and wages in Lima between 2016 and 2018, using employment survey data for Lima, suggesting women and workers with lower education levels have larger reductions relative to other worker groups. Both Morales and Pierola (2020) and Groeger et al. (2024) use spatial variation in the settlement of

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2 Assignment models of the labor market are related as well to the Roy model of job sorting according to job-relevant skills, named after Roy (1951), and formally developed by Borjas (1987), who applied it to the issue of self-selection of migrants.

3 During this episode, 125,000 Cubans fleeing Castro’s regime reached the city of Miami, which experienced an increase in its labor force of 7%, particularly in low-skilled occupations and industries.

4 Lewis (2004) provides some evidence that the production technology adjusted to the mix of workers as well.

5 Peri and Yasenov’s (2019) research was partly motivated by recent controversy about Card’s (1990) seminal work; see, e.g., Borjas (2017) and Clemens and Hunt (2019).

6 See also Peri et al. (2020) for another application of synthetic control methods.
Venezuelan migrants a decade prior (in 2007) to the mass migration in Peru (in 2017) to identify the labor market effects of migration. While using similar econometric strategies and similar data, the two studies find conflicting effects on employment and income. Morales and Pierola (2020) find no overall significant effects on employment, formality, or individual earnings whereas Groeger et al. (2024) find positive and significant effects of Venezuelan migration on both income and employment of men and women, with particularly large effects for women.\footnote{We note that the total number of Venezuelan migrants in Peru in 2007 was less than 3,000 (CEPAL 2023), and thus that this spatial variation may not be a good predictor of Venezuelans post mass migration, although Groeger et al. (2024) argue the first stage shows good predictive power of the instrument.}

Other episodes of mass migration that have received attention in recent literature include out migration from the Soviet Union and the former GDR to Germany and Israel (Cohen-Goldner and Paserman 2006; D’Amuri et al. 2010; De New and Zimmermann 1994; Friedberg 2001), Syrian refugees in Jordan and Turkey (Altindag et al. 2020; Del Carpio and Wagner, 2015; Fallah et al. 2019), and Nicaraguan refugees in Costa Rica (Gindling 2009).\footnote{A related example of South-South migration is seen for Ecuador’s policy of universal travel freedom that led to a significant increase of immigration from previously restricted nationalities in Africa, Asia, and the Caribbean (Freier and Holloway 2019).} Overall, as pointed out by Clemens and Hunt (2019: 3), “the evidence from refugee waves reinforces the existing consensus that the impact of immigration on average native-born workers is small, and fails to substantiate claims of large detrimental impacts on workers with less than high school.”\footnote{See Hanson (2009) for a general review of the empirical literature on the impact of migration on welfare.}

The remainder of this paper is organized as follows. In Section 2 we provide background information on the Venezuelan exodus and their arrival to Peru. In Section 3 we describe our theoretical model. In Section 4 we describe the data, sample, and identification strategy. In Section 5 we present the results. In Section 6 we gather concluding remarks.

## 2 VENEZUELAN EXODUS IN PERU

Over five million individuals left Venezuela between 2016 and 2020 as a result of the political, socioeconomic, and humanitarian crisis in the country (Chaves-González and Echevarría Estrada 2020). The main destination countries are Colombia, Peru, Ecuador, and Chile, with Venezuelan migrants constituting between 2 and 3% of the local population (see Table 1). Migration to these countries has been facilitated by the commonality of language and relatively open-door policies.

<table>
<thead>
<tr>
<th>COUNTRY</th>
<th>VENEZUELAN MIGRANTS</th>
<th>POPULATION (MILLION)</th>
<th>SHARE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colombia</td>
<td>1,400,000</td>
<td>50.3</td>
<td>2.75</td>
</tr>
<tr>
<td>Peru</td>
<td>870,000</td>
<td>32.5</td>
<td>2.63</td>
</tr>
<tr>
<td>Ecuador</td>
<td>385,000</td>
<td>17.4</td>
<td>2.19</td>
</tr>
<tr>
<td>Chile</td>
<td>371,000</td>
<td>19.0</td>
<td>1.94</td>
</tr>
<tr>
<td>United States</td>
<td>351,000</td>
<td>329.0</td>
<td>0.01</td>
</tr>
<tr>
<td>Brazil</td>
<td>224,000</td>
<td>211.0</td>
<td>0.11</td>
</tr>
<tr>
<td>Argentina</td>
<td>145,000</td>
<td>44.8</td>
<td>0.32</td>
</tr>
<tr>
<td>Panama</td>
<td>94,000</td>
<td>4.2</td>
<td>2.19</td>
</tr>
</tbody>
</table>

Before 2017 there were only about 60,000 Venezuelans in Peru (Mendoza and Miranda 2019). From 2017 to 2019 nearly 800,000 Venezuelans arrived to the country (The World Bank 2019b).\footnote{By 2020, according to R4V (2020), the number of Venezuelan migrants and refugees in Peru reached 1,100,000.} About 84.5% arrived by bus covering 4,500 km in a trajectory that takes several days. Survey data indicate (INEI 2019a), about 42% of migrants are between 18 and 29 years old and 90% are under
50 years old. The gender composition is balanced (48% of migrants are females), and about 75% of migrants arrive with their families; there are about 117,000 infants among the migrants.

The Peruvian government implemented a temporary residence permit program in 2017 (“permiso temporal de permanencia” or PTP) to address the immigrant crisis, influenced by a similar program in Colombia. The PTP allows migrants to reside, work, study, open a bank account, and pay taxes in a regular way for a year. Through the PTP and a panoply of refugee permits and other visa instruments, about 96.7% of the migrants have some legal status (INEI 2019a).11

The legal open-door policy toward Venezuelans in Peru does not necessarily imply acceptance or a lack of discrimination. Survey data shows that by the end of 2019, 76% and 77% of individuals in Lima agreed that “Venezuelans are taking away jobs from many Peruvians” and “The arrival of so many Venezuelans will harm the economy of Peruvians,” respectively (IOP-PUCP 2020). Survey data from 2019–2020 shows that in cities like Lima, Tacna, and Trujillo, over 70% of Venezuelans report having experienced nationality-based xenophobia, particularly at work or when looking for a job (Freier and Pérez 2021).

Venezuelan migrants settled mostly in the coastal area of Peru. According to data from residence permit applications (The World Bank 2019b), about 84% of all migrants settled in the metropolitan area of Lima, including the capital city of Lima and the adjacent port of Callao, about 4% in Trujillo, 3% in Arequipa, and much smaller percentages in other urban areas (see Table 2). Metropolitan Lima is home to 32% of the Peruvian population and accounts for nearly 48% of GDP. In comparison, Trujillo and Arequipa each have one tenth of the population of Lima and account for 4% and 7% of GDP respectively (INEI 2019d). Table 2 further shows Venezuelan migrants as a proportion of the total population for other cities in Peru was much smaller than the case for Lima. Thus, migrants settled much more than proportionally in Lima in relation to population and economic activity. Absent previous migrant networks, Lima was an obvious destination for recent arrivals.12 By December 2018, Venezuelan migrants were about 10% of the population over the age of 18 working or looking for a job in metropolitan Lima (see Figure 1).

<table>
<thead>
<tr>
<th>DEPARTMENT</th>
<th>% SHARE OF VENEZUELAN MIGRANTS</th>
<th>% SHARE OF DEPARTMENT POPULATION</th>
<th>% SHARE OF CITY POPULATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lima – Callao (Lima)</td>
<td>83.8</td>
<td>6.9</td>
<td>6.9</td>
</tr>
<tr>
<td>La Libertad (Trujillo)</td>
<td>3.9</td>
<td>2.1</td>
<td>3.8</td>
</tr>
<tr>
<td>Arequipa (Arequipa)</td>
<td>3.0</td>
<td>0.7</td>
<td>2.5</td>
</tr>
<tr>
<td>Lambayeque (Chiclayo)</td>
<td>1.2</td>
<td>0.7</td>
<td>1.8</td>
</tr>
<tr>
<td>Piura (Piura)</td>
<td>1.4</td>
<td>0.3</td>
<td>2.3</td>
</tr>
<tr>
<td>Ancash (Chimbote)</td>
<td>1.3</td>
<td>0.4</td>
<td>2.7</td>
</tr>
<tr>
<td>Cusco (Cusco)</td>
<td>0.5</td>
<td>0.3</td>
<td>0.9</td>
</tr>
<tr>
<td>Ica (Ica)</td>
<td>1.6</td>
<td>0.4</td>
<td>4.1</td>
</tr>
<tr>
<td>Tacna (Tacna)</td>
<td>0.5</td>
<td>1.1</td>
<td>1.4</td>
</tr>
<tr>
<td>Tumbes (Tumbes)</td>
<td>0.5</td>
<td>1.5</td>
<td>3.9</td>
</tr>
<tr>
<td>Junin (Huancayo)</td>
<td>0.3</td>
<td>0.2</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Working age migrants are on average more educated than the local population in the Lima metropolitan area and in Peru at large (see Table 3). About 58% of migrants have more than high school education, and about 39% have at least some college education. The respective percentages are 43% and 24% for Lima, and 34% and 19% for Peru.

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11 See Blouin and Freier (2019) for a detailed description of the PTP.

12 In Ecuador and Chile, Venezuelan migrants also settled in the cities with most economic activity. In Colombia there was an important influx to border areas (The World Bank 2018).

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Table 2 Distribution of Venezuelan migrants in Peru (June 2019).

Notes: Peru is administratively divided into 24 departments plus the Callao province (which is treated as a department and is contained in the metropolitan area of Lima). The most populous city of each department is in parenthesis. To calculate the share of Venezuelan migrants at the city level we assigned all migrants in the Department to the city. (Note that while the Departments of Ica, Tacna, and Tumbes have information for the number of Venezuelan migrants, their main city is not one of the most populated Peruvian metropolitan areas and as such are not part of the donor pool used in our empirical estimations. Sources: The World Bank (2019b) and Bacigalupo and Goldstein (2019).
The vast majority of working age migrants in Peru are employed with 90% employed compared to about 70% of Peruvians (INEI 2019a). The unemployment rate for migrants is 6%, very similar to the rate of locals—and much lower than migrants in Colombia, where Venezuelans have an unemployment rate of 22%. About half of Venezuelans in Peru were employed in hotels, restaurants, and retail industries, where hiring may be more flexible; about 84% of the total employment in these industries is informal (The World Bank 2019b).

Table 4 compares the occupations of Venezuelan migrants in comparison with those of the Peruvian urban population. The education level of Venezuelan migrants is higher on average than that of Peruvians. However, as the table demonstrates, there is a larger proportion of Venezuelan migrants in elemental jobs. This seems, consistent with some “downgrading” of the migrants’ skills (The World Bank 2019b). Relatedly, the skill sets of Venezuelan migrants may not all be easily transferred to the Peruvian context, which particularly for the professional sector might constrain potential effects of Venezuelan migration on this sector. Professional licensing in Peru, depending on the occupation, can include several steps, including 1) receiving a temporary residency permit 2) obtaining validation of the degree by the Peruvian government agency that does the validation of foreign credentials (SUNEDU) and 3) passing a credentialing exam if required (Chaves-González and Delgado 2023). The ENPOVE rounds ask Venezuelan migrants if they have been able to revalidate their education degrees for those with a completed undergraduate or graduate degree. Only 3.4% in the ENPOVE 2018 of those migrants respond yes. Licensing barriers are, however, likely less important in economic activities where informality is pervasive, like services, where about a third of Venezuelan migrants work.

Table 3 Education level of Venezuelan migrants and Peruvians (%).

<table>
<thead>
<tr>
<th>Education</th>
<th>Venezuelan Migrants</th>
<th>Lima</th>
<th>Peru</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic or no schooling</td>
<td>1.5</td>
<td>5.1</td>
<td></td>
</tr>
<tr>
<td>Primary school</td>
<td>10.2</td>
<td>10.3</td>
<td>19.1</td>
</tr>
<tr>
<td>High school</td>
<td>31.9</td>
<td>45.1</td>
<td>42.3</td>
</tr>
<tr>
<td>Vocational school</td>
<td>19.2</td>
<td>18.2</td>
<td>14.2</td>
</tr>
<tr>
<td>Some college</td>
<td>13.0</td>
<td>8.9</td>
<td>6.6</td>
</tr>
<tr>
<td>College (complete)</td>
<td>25.7</td>
<td>13.6</td>
<td>11.1</td>
</tr>
<tr>
<td>Graduate studies</td>
<td>0.7</td>
<td>2.3</td>
<td>1.5</td>
</tr>
</tbody>
</table>

The vast majority of working age migrants in Peru are employed with 90% employed compared to about 70% of Peruvians (INEI 2019a). The unemployment rate for migrants is 6%, very similar to the rate of locals—and much lower than migrants in Colombia, where Venezuelans have an unemployment rate of 22%. About half of Venezuelans in Peru were employed in hotels, restaurants, and retail industries, where hiring may be more flexible; about 84% of the total employment in these industries is informal (The World Bank 2019b).

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13 Survey data from UN Migration (Chaves-González and Echevarría Estrada 2020) identifies three groups of countries that attract different migrant profiles. For border countries (Brazil, Colombia, Guyana, and Trinidad and Tobago), migrants are mostly young and single, have low educational attainment and have a larger intention to eventually return to Venezuela compared to the other groups. For Peru and Ecuador, migrants are also young but with higher education and often migrate with their families. Finally, the group composed of Argentina, Chile, Paraguay, Uruguay, and Costa Rica have older migrants as well as the highest education levels.

14 The ILO and United Nations have recently proposed a Socio-Economic Regional Integration Strategy (Hidalgo et al. 2021), which includes among other components the “validation of technical and academic qualifications” to facilitate the integration of Venezuelan migrants to the labor market.
Given the greater level of schooling of Venezuelan migrants compared with the local labor force, we conjecture that their integration to the job market could reduce the premium for education-related skills, and at the margin displace some of the local labor force to jobs where those skills are less relevant. In the following sections, we propose a model that allows for such displacement to occur and conduct an estimation of the effects of the migration on sectoral employment and working conditions of the local population in Lima.

3 A MODEL OF EMPLOYMENT AND MIGRATION

We use a simple sector assignment model to analyze the effects of migration on employment and earnings. We first develop the basics of the model, and then introduce migration as a labor shock.

3.1 EMPLOYMENT, SALARIES, AND EARNINGS

Consider an economy with two sectors, 1 (low-skilled jobs) and 2 (high-skilled jobs), and a continuum of workers of mass \( \mu \). Each worker in the economy has some skill level \( s \). Workers’ skills are distributed according to some continuous probability density \( \phi \) with support given by some interval \([s, \overline{s}]\). The effective labor that a worker can contribute to one sector or the other depends on skill level according to a mapping \( x(s) = (x_1(s), x_2(s)) \in [0, 1]^2 \), where \( x_j(s) / x_i(s) \) is continuous in \( s \) and strictly increasing for \( s \in [s, \overline{s}] \). In other words, more skilled workers are relatively better at working in sector 2.

Each worker can work in sector 1 or 2. An assignment is a partition \( (L_1, L_2) \) of the set of possible skills \([s, \overline{s}]\) so that all workers with skills in \( L_j \) work in sector \( j = 1, 2 \). The output in each sector depends on the mass of workers who are employed in the sector and their effective labor, and is given by

\[
X_j = \mu \int_{s \in L_j} x_j(s)\phi(s)ds.
\]

The two sectors serve as inputs in the production of a consumption good by a representative firm, according to the production function \( F(X_1, X_2) \), satisfying the usual properties: \( F \) is strictly increasing, strictly quasiconcave, continuously differentiable, and linearly homogeneous (i.e., there are constant returns to scale). Thus, the partial derivatives \( F_1 \) and \( F_2 \) depend only on the ratio \( X_1 / X_2 \) and are respectively strictly decreasing and strictly increasing in this ratio. To avoid corner equilibria, we assume that \( F_1 \) and \( F_2 \) grow unboundedly as \( X_1 / X_2 \) and \( X_2 / X_1 \) go to zero, respectively.

Let \( w_1 \) and \( w_2 \) represent, respectively, the salary offered in sector 1 and 2 per unit of effective labor in units of the consumption good, so that the earnings of a worker with skill \( s \) are either \( w_1 x_1(s) \) or \( w_2 x_2(s) \), depending on the worker’s choice of sector. Note that we normalize the price of the consumption good to one.

A competitive equilibrium is a salary pair \((w_1, w_2)\) and an assignment \((L_1, L_2)\) such that
(i) each worker gets employed in the sector leading to larger earnings, \(^\text{15}\) that is,

\[
L_1 = \left\{ s \in [s, \bar{s}] : \frac{x_j(s)}{x_i(s)} < \frac{w_1}{w_2} \right\} \quad \text{and} \quad L_2 = \left\{ s \in [s, \bar{s}] : \frac{x_j(s)}{x_i(s)} \geq \frac{w_1}{w_2} \right\},
\]

and

(ii) each worker is paid their marginal product, that is

\[
w_1 = F_1(X_1, X_2) \quad \text{and} \quad w_2 = F_2(X_1, X_2).
\]

Since \( F \) is linearly homogeneous, \( F(X_1, X_2) = F_1(X_1, X_2)X_1 + F_2(X_1, X_2)X_2 \). Thus, if workers are paid their marginal product, as required by the equilibrium definition, profits in the economy are zero. Consequently, we do not need to specify property shares of the representative firm.

To understand the equilibrium construction, note that any \( s \in [s, \bar{s}] \) provides a partition of the set of workers given by \( L_1(s) = [s, s] \) (possibly empty) and \( L_2(s) = [s, \bar{s}] \). Let also

\[
X_j(s) = \mu \int_{z \in \mathbb{L}_j(s)} x_j(z) \phi(z)dz
\]

represent the output in sector \( j = 1, 2 \) induced by the cutoff skill \( s \). Using conditions (i) and (ii), \( (L_1(s), L_2(s)) \) is an equilibrium assignment if

\[
\frac{x_j(s)}{x_i(s)} = \frac{w_1}{w_2} \quad \text{and} \quad \frac{w_1}{w_2} = \frac{F_1(X_1(s), X_2(s))}{F_2(X_1(s), X_2(s))}
\]

which together imply

\[
\frac{x_j(s)}{x_i(s)} = \frac{F_1(X_1(s), X_2(s))}{F_2(X_1(s), X_2(s))}. \tag{1}
\]

The expression in the left-hand side is by assumption nonnegative and strictly increasing in \( s \), while the expression in the right-hand side is positive and strictly decreasing in \( s \), and is arbitrarily large for \( s \) close to \( \bar{s} \) and arbitrarily close to zero for \( s \) close to \( s \). By standard arguments, there is a unique solution \( s^* \) to equation 1, and \( (L_1(s^*), L_2(s^*)) \) is the unique equilibrium assignment.

### 3.2 SKILLED MIGRATION

Let the original population of workers be of mass 1 and distribution of skills \( \phi_n \), and let the migrant population be of mass \( m \) and distribution of skills \( \phi_m \).

To analyze the impact of migration, we define

\[
x(s) \equiv \frac{x_j(s)}{x_i(s)}
\]

to be the skill ratio for the marginal worker,

\[
T(X_1 / X_2) \equiv \frac{X_j(X_1, X_2)}{X_i(X_1, X_2)}
\]

to be the marginal rate of transformation between sectors, and

\[
X(s, m) \equiv \frac{X_{jn}(s) + mx_{jn}(s)}{X_{jn}(s) + mX_{jn}(s)}
\]

to be the ratio of effective labor, where

\[
X_{jn}(s) = \int_{z \in \mathbb{L}_j(s)} x_j(z) \phi_n(z)dz \quad \text{and} \quad X_{jm}(s) = \int_{z \in \mathbb{L}_j(s)} x_j(z) \phi_m(z)dz
\]

represent per capita effective labor offered by the local and the migrant labor force respectively in sector \( j = 1, 2 \).

---

\(^{15}\) The set of workers who are indifferent has measure zero; we simply allocate them to sector 2.
We can rewrite equilibrium condition 1 as
\[ x(s) = T(X(s, m)). \]

Using the implicit function theorem, we can calculate the marginal effect of migration on the equilibrium relative salary of low-skilled labor (given by \( w_1/w_2 = x(s) \)), as
\[
\frac{d(w_1/w_2)}{dm} = x'(s) \frac{ds}{dm} + \frac{(T's)(\partial_x X - T's)}{X'(s)}.
\]

The direct effect is the change in the salary ratio if there is no reallocation of labor, while the indirect effect is the effect of reallocation, running counter. Similarly, we can calculate the marginal effect of migration on sector employment of the local labor force as
\[
\frac{d(X_{1n}/X_{2n})}{dm} = \partial_z (X_{1n}/X_{2n}) \frac{ds}{dm}.
\]

Near \( m = 0 \), we have
\[
\partial_m X = \frac{X_{2n}}{X_{2m}} \left( \frac{X_{1m} - X_{1n}}{X_{2m} - X_{2n}} \right),
\]
which is negative as long as the migrant labor force is relatively skilled compared to the local labor force, that is,
\[
\frac{X_{1m}}{X_{2m}} < \frac{X_{1n}}{X_{2n}}.
\]

We also have
\[
\partial_z X = \partial_z (X_{1n}/X_{2n}) = \frac{X_{1n}}{X_{2n}} \left( \frac{X_1(s^*)}{X_1} - \frac{X_1(s^*)}{X_2} \right) \phi(s^*) > 0.
\]

We can check that, if condition C is satisfied, the direct effect over relative salaries is negative and larger in absolute value than the indirect effect. Thus, the result of skilled migration is an increase in the relative salary of low-skilled labor and an increase in the ratio of low-skilled labor within the local population.

If \( \phi(s^*) \) is near zero (the canonical case in the migration literature), the effect of migration on salaries is just the direct effect, and there is no effect on employment. That is, expressing the effects of migration as percent changes, as \( s \) goes to zero
\[
\frac{d(w_1/w_2)}{w_1/w_2} \approx 0,
\]
and
\[
\frac{d(X_{1n}/X_{2n})}{X_{1n}/X_{2n}} \approx 0,
\]
where \( \sigma \) is the elasticity of substitution derived from \( F \).

Per contra, as \( \phi(s) \) grows large near the initial cutoff, the effect of migration on salaries becomes negligible and local employment accommodates the effect of migration, that is
\[
\frac{d(w_1/w_2)}{w_1/w_2} \approx 0,
\]
and
\[
\frac{d(X_{1n}/X_{2n})}{X_{1n}/X_{2n}} \approx 0.
\]

Equations 4 and 5, multiplied by the share of migrants, provide upper bounds to the percent change in the salary ratio of low-skilled versus high-skilled labor, and the change in the ratio of effective employment in the low-skilled versus high-skilled sector. Actual average earnings and actual employment (number of workers) in each sector are different than salary rates and
effective units of labor due to heterogeneity in productivity. With that caveat in place, we can approximate the skill advantage of the Venezuelan migration using the fraction of the migrants \( m \) and the local (Lima) labor force \( n \) with more than high school (that is, those with vocational school, some college, complete college and graduate studies) as \( X_2 \) and the remainder as \( X_1 \) (see Table 3); this suggests that

\[
\frac{X_{2m}}{X_{2n}} - \frac{X_{1m}}{X_{1n}}
\]

is approximately 0.63. That is, with small or negligible movements in relative salaries, one should expect a migration shock of 10% of the labor force to imply a change in the ratio of local effective employment in the low-skilled versus the high-skilled sector of 0.063. Therefore, considering an initial ratio of around 1.32, migration implies a movement of about 2.6% of the local labor force to low-skilled jobs.

Figure 2 illustrates the effect of migration on equilibrium salaries and employment. Relatively skilled migration leads to an increase in the marginal rate of transformation between sectors; the old marginal rate of transformation is given by the continuous decreasing line and the new by the dashed decreasing line in blue. The direct effect on the relative salary in the low-skilled sector is given by \( b-a \), and the indirect effect by \(- (b-c)\). If \( \phi(s^*) \) is close to zero, the marginal rate of transformation is nearly horizontal around \( s^* \), and the indirect effect is near zero. Per contra, if \( \phi(s^*) \) is large, the marginal rate of transformation is nearly vertical around \( s^* \), and the indirect effect is nearly equal in absolute value to the direct effect.

Figure 3 illustrates the effect of migration on equilibrium production. The production possibility frontier is obtained by varying \( s \) from \( s \) (all labor is assigned to sector 2) to \( s \) (all labor is assigned to sector 1), and the isoquants are obtained from the function \( F \). Relatively skilled migration leads to an expansion of the production possibility frontier biased in the direction of sector 2. If the initial cutoff is not adjusted, skilled migration increases inefficiently production in sector 2, as illustrated by point \( b \); further adjustment of labor in the direction of sector 1 leads the economy to point \( c \). The slope of the isoquants at points \( a \), \( b \), and \( c \) in Figure 3 are given respectively by points \( a \), \( b \), and \( c \) in Figure 2. If \( \phi \) is large at the initial cutoff, the production possibility frontier is nearly linear at point \( a \), so that after an expansion the economy returns to nearly the same ray \( X_1/X_2 \).
4 DATA AND EMPIRICAL STRATEGY

4.1 DATABASE AND SAMPLE

Our data comes from the cross-sectional component of the Peruvian national household survey, the ENAHO (for its name in Spanish). We work with households in the database between January 2013, four years before the influx of mass Venezuelan migration, and December 2019. The ENAHO covers both the urban and rural areas of Peru and is collected continuously over 12 months. The cross-section component of the ENAHO has a yearly average of 35,000 households. Urban households make up 70% of the total survey.

We use the cross-sectional variation of the ENAHO. We restrict the sample to Peruvian-born individuals, aged 18–75, who reside in the nine largest metropolitan areas of Peru. The metropolitan areas included are Lima, Arequipa, Trujillo, Chiclayo, Piura, Iquitos, Cusco, Chimbote, and Huancayo (see Figure 4).

The total sample consists of 138,013 observations, of which just over half (51.5%) belong to Lima, and the other half is distributed in the rest of the metropolitan areas (see Table 5). Table 6 shows the descriptive statistics of Lima versus other metropolitan areas in our sample, before the influx of Venezuelan migrants. The labor market outcomes that we analyze include employment, hours worked in the principal activity, informal work (defined by the ENAHO as workers with no contribution to the pension scheme), labor income per hour, and occupation distribution.

Occupations are classified as professional jobs (legislators, senior officials, and managers; scientific, engineering, and related professionals; life science and health professionals; teaching professionals; business professionals; social sciences professionals; legal professionals), white-
collar jobs (technicians and associate professionals; office clerks; service workers; shop and market sales workers), blue-collar jobs (skilled agricultural and fishery workers; craft and related trades workers; plant and machine operators; assembly workers), and unskilled jobs (domestic work; street vendors; building caretakers; messengers; porters; garbage collectors).20

Figure 4 Most populated Peruvian metropolitan areas.

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As shown by Table 6, Lima is similar in most outcomes to other areas before the migration shock, although the share of informal workers is smaller in Lima, and the monthly income in constant soles is higher.\textsuperscript{21,22}

To adjust for different living expenses across cities, we multiply income by the ratio between the consumer price index of each city and that of Lima.

The share of unskilled workers both in Lima and in other metropolitan areas is much smaller than the fraction of the local labor force with high school or less education. That is, some jobs that are classified as blue-collar or white-collar can be performed by workers without technical or college education so they can be considered as well, in terms of the model, as relatively low-skilled jobs (see Figure 5a). In other words, low-skilled jobs cut across different occupational categories and therefore in our analysis we use the above four mentioned groups.

Table 5 Sample distribution. 
Source: Own calculations based on INEI (2019b).

Table 6 Descriptive statistics (before 2017). 
Source: Own calculations based on INEI (2019b).
4.2 EMPIRICAL STRATEGY

Following the recent work of Peri and Yasenov (2019), our approach is based on the Synthetic Control Method (SCM). The SCM compares the evolution of an aggregate outcome for a “treated” unit to the evolution of the same outcome for some control group, constructed as a weighted average of the set of control or “donor” units and called the “synthetic control.” SCM models choose a set of weights which when applied to a group of corresponding units produce an optimally estimated counterfactual to the unit that received the treatment. More weight is given to units in the donor pool that are similar to the treatment one in terms of covariates that are predictive of post-intervention outcomes and pre-intervention outcome values. (Billy and Packard 2020).

Following Abadie and Gardeazabal (2003), Abadie et al. (2010), Abadie et al. (2015), and Peri and Yasenov (2019), we consider nine metropolitan areas indexed by \( j = 0, 1, 2, \ldots, 8 \) and denote Lima as 0, while we call the group of all the rest the “donor pool.” We define a vector \( \mathbf{G}_0 \) of dimension \( k \times 1 \) whose elements are equal to the values of variables that help predict our outcomes in Lima between the first semester of 2013 and the second semester of 2016, before the influx of Venezuelan migrants. We define a \( k \times 8 \) matrix, \( \mathbf{G} \), in which row \( j \) is the sequence of values for the same variables and semesters relative to city \( j \) in the “donor pool.” We identify the vector of nonnegative weights \( \mathbf{W}^* = (w_1, \ldots, w_8) \) that produces a convex combination of variables in cities in the donor pool, \( \mathbf{G} \), to approximate as close as possible, in terms of a quadratic error, the pre-treatment vector of variables chosen for Lima, \( \mathbf{G}_0 \). That is, we select the weights that minimize the distance in each semester for the values of variables that help predict our outcomes before the influx of Venezuelans between Lima and synthetic Lima, made up of all the other metropolitan areas. We minimize the distance for the outcome under analysis, share of high school graduates, share of 18–35 years old, share of unskilled workers, share of retail workers, and unemployment rate before 2017, that is, pre-migration.

Finally, following Peri and Yasenov (2019), we adjust each outcome using the following regression in order to reduce the potential confounding effects from differential demographic characteristics in the labor market:

\[
y_{it} = \alpha + \beta_1 \text{Age}_{it} + \beta_2 \text{Men}_{it} + \beta_3 \text{Edu}_{it} + \delta_i + \gamma_1 (\text{Age}_{it} \times \delta_i) + \gamma_2 (\text{Men}_{it} \times \delta_i) + \gamma_3 (\text{Edu}_{it} \times \delta_i) + \epsilon_{it},
\]

where \( \text{Age}_{it} \) is a dummy that takes the value of 1 for individuals older than 41 (the median age); \( \text{Men}_{it} \) takes the value of 1 for men; \( \text{Edu}_{it} \) is a dummy for those with more than high school education, and \( \delta_i \) are a series of two-semester dummies. This produces, for each outcome under analysis, a residual \( \epsilon_{it} \) that captures individual variation once the aggregate trends are controlled for. For our specifications, we average these residuals by semester and metropolitan area and treat them as the outcome variable.

---

\( W^\star \) is chosen to minimize \( \mathbf{G}_0 - \mathbf{GW} \), that is \( W^\star = \arg \min (\mathbf{G}_0 - \mathbf{GW})^\prime \mathbf{V} (\mathbf{G}_0 - \mathbf{GW}) \) subject to \( \sum_{j=1}^{8} w_j = 1 \) and \( w_j \geq 0 \). The weighting matrix \( \mathbf{V} \) is chosen to minimize the mean squared predicted error of the outcome before the migrant influx, that is \( \mathbf{V}^\star = \arg \min (1/J) \sum_{j=1}^{8} ||\tilde{Y}_j - \hat{Y}_j (\mathbf{V})||^2 \), where \( t \) is the first semester of 2013, \( \tilde{T} \) is the second semester of 2016, the period before the influx, and \( \hat{Y}_j = \sum_{j=1}^{8} w_j Y_{jt} \), where \( w_j \geq 0 \) and \( \sum_{j=1}^{8} w_j = 1 \).
To determine the quality of matches between Lima and its synthetic control, we perform both a visual inspection as well as compare the balance among predictors between the two units. **Figure 6** demonstrates prior to the Venezuelan migration, the levels between Lima and the synthetic control are very similar for labor market participation, hours worked, as well as the

**Figure 6** Impact of Venezuelan migration on labor market outcomes in Lima, synthetic control results, age 18–75. **Source:** Own calculations based on INEI (2019b).

**Notes:** Each sub-figure shows the outcome variable for Lima (solid line) and synthetic control (dashed line) in the period 2013–2019. Migration starts first semester of 2017 (vertical line). Donor weights in Table A.6.
different types of occupations.\textsuperscript{24} Predictor balance in Table A.3 in the Appendix also suggest the synthetic control tracks well with Lima.

As we noted earlier, migration to cities besides Lima is not insignificant, but generally much lower than migration to Lima (Table 2). However, to reduce concerns that we under-estimate the impacts of migration, we consider an alternative synthetic control composed of cities with an influx of Venezuelan migrants of less than 3% of their population. We also acknowledge that city of settlement may be viewed as a choice, raising the possible concern that unobserved labor market shocks could impact both immigrants’ outcomes and their decision to settle in Lima. While we cannot model choice of migrant destination, we carry out an additional robustness test where we define the synthetic control for Lima to be only cities south of Lima, which presumably have higher costs of migration for Venezuelan migrants as they are further away from the Northern border of Peru where most Venezuelan migrants enter the country.

5 RESULTS

5.1 MAIN RESULTS

Figure 6 presents outcome variables for Lima and its synthetic control for labor market measures in our sample. After the first semester of 2017 when the Venezuelan migration begins, the outcome trends for employment (donor weights: Arequipa 74.1%, Chimbote 25.4%, Huancayo 0.4%)\textsuperscript{25} and hours in principal activities (donor weights: Arequipa 59.1%, Chiclayo 4.9%, Huancayo 19.8%, Piura 16.2%) do not separate from their synthetic control, suggesting little effect of the influx of Venezuelans on these variables. For the natural logarithm of labor income per hour (donor weights: Arequipa 100%), we also do not observe differences between employees in Lima and the synthetic. Analysis of occupation structure, however, suggests larger effects of the migration. In particular, Figure 6 suggests there is a decrease in those employed in white-collar jobs (donor weights: Arequipa 46.5%, Huancayo 34.1%, Piura 19.4%) and blue-collar jobs (donor weights: Arequipa 46.1%, Chiclayo 0.3%, Huancayo 29.3%, Piura 24.3%) in Lima, and an increase in those employed unskilled jobs (donor weights: Arequipa 71.9%, Chimbote 22.1%, Trujillo 6.1%). The differences grow over time, consistent with the larger number of migrants continuing to arrive post 2017. While we see little change for the share in professional jobs post migration, we see a separation of trends between treatment and synthetic control for the shares of white-collar jobs, blue-collar jobs, and, particularly, unskilled jobs.

Following Peri and Yasenov (2019), to quantify these graphical effects we estimate:

\[
y_{ct} = \alpha + \beta_1 (\text{Lima}_c \times \text{After}_t) + \beta_2 (\text{Lima}_c \times \text{After}_t) + \text{After}_t + \text{Lima}_c + \epsilon_{ct},
\]

where \(y_{ct}\) is the outcome of interest in metropolitan area \(c\) in period \(t\); \(\text{Lima}_c\) is a dummy equal to one for Lima and zero for the synthetic control; \(\text{After}_t\) is a dummy equal to one for observations in the first semester of 2017, second semester of 2017 or first semester of 2018; and \(\text{After}_t\) is a dummy equal to one for observations in the second semester of 2018, first semester of 2019 or second semester of 2019. The method of estimation is feasible generalized least squares (FGLS), with AR (1) errors. Table 7, column (1) shows the results, which are generally consistent with Figure 6.\textsuperscript{26} The increase in share of local workers in unskilled jobs from the pre-migration period to the second semester of 2018 onwards is about 3 percentage points, near the 2.3 percentage points for that period according to the difference in differences estimation in Table A.4. This is in the ballpark of the upper bound found from the model in the absence of significant movements in relative salaries (also observed in Table 6). We see that the previous increase in unskilled jobs is fueled in part by a decrease in white-collar jobs (around 2.6 percentage points) and of blue-collar ones (1 percentage point). Table A.5 shows the results for the different outcomes analyzed.

\textsuperscript{24} Our estimations are not a good match for informality, probably due to the noise inherent to such variable. Given that informality is a legal term related to contributions to the pension scheme, we also created a new informal variable defined as those who do not have access to health benefits. While the synthetic control for this variable resembles more Lima, it still lacks the suitability present for the other variables under analysis.

\textsuperscript{25} We also analyze labor force participation and find similar results.

\textsuperscript{26} As noted by Peri and Yasenov (2019), the reduced sample size and the dependence among observations means that we can only be suggestive on inference.
### Table 7: Impact of Venezuelan migration on labor markets in Lima: Regression estimate results 2013–2019, age 18 to 75.

Source: Own calculations based on INEI (2019b). Note: Each column represents a regression of semester observations for Lima and the corresponding synthetic control between 2013 and 2019 for different samples. Each specification includes city and period dummies. Each period dummy extends for three semesters. The interaction coefficients between a dummy variable for Lima and a period dummy after migration are reported. The method of estimation is FGLS with AR1 process for the error term assumed * p < 0.05; ** p < 0.01; *** p < 0.001.

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In Figure 7(a) we report the ratio of the logarithm of salaries in professional, white-collar and blue-collar jobs in relation to unskilled jobs, using the average for salary earners (“asalariados”). In Figure 7(b) we report the ratio of the logarithm of average earnings for the same categories. We can consider these as approximations for the ratio of skilled to unskilled salaries in terms of the theory, with the proviso that, as previously noted, some jobs classified as blue-collar or white-collar can be performed with little formal education and would be closer to the theoretical definition of unskilled. There is no evidence in either case of a reduction in the skill due to migration.

Our evidence thus far suggests that the influx of Venezuelans did not lead to large changes in employment, hours worked or relative salaries, but did lead to larger changes in the structure of the Peruvian labor market by shifting workers from white- or blue-collar jobs to unskilled ones. Such movement also correlates with the distribution of education levels within each occupation group, as shown in previous Figures 5(a) and 5(b). In Lima, there is an increase in local workers with tertiary (some college or more) and secondary (high school) education in unskilled jobs in 2019 compared to 2016 that is not seen in other metropolitan areas.
5.2 RESULTS BY GENDER

Figures 8 and 9 show our outcome variables for Lima and its synthetic control for men and women respectively. In general, the figures show that prior to the influx of Venezuelan migrants, the trends for Lima and its counterfactual track closely with each other.27 Tables A.7 and A.8 in the Appendix show the predictor balance.

Figure 8 shows that for Peruvian men in Lima, the migration of Venezuelans did not lead to large changes in employment (donor weights; Arequipa: 63%, Trujillo 37%), hours (donor weights: 67.6%, Chiclayo 24.2%, Huancayo 3%, Piura 5.2%), labor income per hour (donor weights: 95.9%, Trujillo 4.1%), and share of the population in professional jobs (donor weights: Arequipa 77.6%, Chiclayo 3%, Chimbote 17.8%, Huancayo 1.6%) or white-collar jobs (donor weights: Arequipa 3.4%, Huancayo 57.8%, Piura 38.8%). However, the migration does appear to have caused an important decrease in the share of blue-collar jobs (donor weights: Arequipa 56.7%, Chiclayo 7.4%, Huancayo 23%, Piura 12.9%), and an increase in unskilled ones (donor weights: Arequipa 80.1%, Trujillo 19.9%), with effects that increase over time. These effects are corroborated in the estimations shown in Table 6, where the increase in the share in unskilled jobs corresponds to about 5 percentage points, mainly due to reductions in blue-collar ones.28

Figure 9 shows a movement from white-collar jobs (donor weights: Arequipa 83.6%, Chiclayo 0.5%, Trujillo 15.9%) to unskilled ones (donor weights: Arequipa 77%, Chiclayo 1.8%, Trujillo 21.1%) for Peruvian women. No changes are seen for professional (donor weights: Arequipa 75.2%, Chiclayo 4.9%, Chimbote 11.8%, Huancayo 1.3%, Trujillo 6.7%) or blue-collar jobs (donor weights: Arequipa 56.4%, Chiclayo 20.2%, Piura 23.2%), or for hours worked (donor weights: Arequipa 79.4%, Chiclayo 4.3%, Huancayo 2.8%, Trujillo 13.5%). However, for employment (donor weights: Arequipa 67.1%, Chiclayo 8.5%, Chimbote 13.7%, Trujillo 10.7%), the trends suggest a slight decrease in employment for women in the first semester of 2019 (the last semester of our analysis). This is also confirmed by Table 6, which shows an increase in the share of women in unskilled jobs from the pre-migration period to the second semester of 2018 onward of almost 2 percentage points, a reduction of similar magnitudes on the share of white-collar workers as well as a reduction in employment.

In Figure 10 we report the ratio of salaries and the ratio of earnings in professional, white-collar, and blue-collar jobs versus unskilled jobs by gender. It is hard to discern a trend, except perhaps a small negative shock for skilled salaries for women. This is consistent with a smaller adjustment in sector employment for women.

27 Except for labor income per hour for women.
28 Column (3) of Table 7 also shows a decrease in professional jobs for men beginning with the second semester of 2018.
Figure 8 Synthetic control, results for men.
Source: Own calculations based on INEI (2019b).
Notes: Each sub-figure shows the outcome variable for Lima (solid line) and synthetic control (dashed line) in the period 2013–2019. Migration starts first semester of 2017 (vertical line). Donor weights in Table A.9.
Figure 9 Synthetic control, results for women.

Source: Own calculations based on INEI (2019b).

Notes: Each sub-figure shows the outcome variable for Lima (solid line) and synthetic control (dashed line) in the period 2013–2019. Migration starts first semester of 2017 (vertical line). Donor weights in Table A.10.
5.3 RESULTS BY AGE AND EDUCATIONAL LEVEL

In Figures 11 and 12, we report the ratio of employment and occupations by age in skilled jobs versus unskilled jobs. The main takeaway from these figures is that the increase in the share of unskilled jobs is concentrated in the older population (41 to 75 years old) with low education (high school or less). Tables A.11 and A.12 in the Appendix show the predictor balance.

5.4 ROBUSTNESS CHECKS

In this subsection, we carry out a number of robustness and sensitivity checks. A first possible concern is that we may underestimate the effects of Venezuelan migration because, as shown in Table 2, some Venezuelan migrants settle in cities outside of Lima, which are part of our synthetic control. Therefore, we re-estimate our synthetic control excluding cities where the population of Venezuelan migrants is larger than 3%. These results are shown in Figure A.1 and are extremely similar to our main results. Secondly, acknowledging that choice of settlement location, while outside the scope of our analysis, may be endogenous, we define the synthetic control group to be only those cities south of Lima. Because the vast majority of migrants from Venezuelan enter from the Northern border, cities south of Lima are significantly more costly to reach. These results (shown in A.2) are also nearly identical to our main results.

Second, following Abadie and Gardeazabal (2003), Abadie et al. (2010), and Peri and Yasenov (2019), we compare our estimated treatment effects against an estimated distribution of placebo effects. That is, we create a synthetic Arequipa, a synthetic Trujillo, and so on, using the other metropolitan areas as potential donors, and simulate treatment effects for each of these cities. For each placebo estimation, Lima is excluded. The grey lines in Figure 13 are the placebo effects or permutations, and the dark one represents our main results for Lima. We use this distribution to provide evidence on whether the probability that we observed the changes in occupational distribution happened by chance or because of the Venezuelan migration.

We observe that for the variables where effects are observed (e.g., on the proportion in white-collar, blue-collar, and unskilled occupations), Lima lies on or near the extreme of the distribution of the simulated permutation effects. Specifically, Lima is on the upper envelope of the distribution of placebo effects for unskilled occupations, supporting our interpretation of impacts due to the migration. In the Appendix, we repeat this exercise by gender, age, and educational level (see Figures A.3, A.4, A.5, and A.6).

Third, following recommendations from Ferman et al. (2020) and Botosaru and Ferman (2019) that show that results for synthetic control estimation which have a limited number of pre-treatment periods may vary substantially according to the specification, we carry out a variety of specifications that vary the inclusion of pre-treatment outcome lags. We also repeat our main specification excluding control variables. Figures A.7 through A.10 replicate our series of graphs using four different specifications, which include 1) no lags of the outcome of interest (Figure A.7), 2) only even lags of the outcome of interest (Figure A.8), 3) only odd lags of the outcome of interest (Figure A.9), and 4) all lags of the outcome of interest (Figure A.10).

29 The same can be seen in Table 7, columns (4)–(7).
Figure 11 Synthetic control, employment and occupations results by age.

Source: Own calculations based on INEI (2019b).

Notes: Each sub-figure shows the outcome variable for Lima (solid line) and synthetic control (dashed line) in the period 2013–2019. Migration starts first semester of 2017 (vertical line).

(Figure A.9, and 4) all lags of the outcome of interest but excluding control variables (Figure A.10). Importantly, our main results remain, and the pre-treatment fit between Lima and synthetic Lima is quite similar for the most part, although in some specifications there is less overlap between Lima and synthetic Lima pre-treatment for the proportion in white-collar and the proportion in blue-
collar jobs. Our results, however, continue to show strong support for little effect of Venezuelan migration on employment and income and an increase in unskilled work due to this migration.

Finally, we run a basic difference-in-difference model comparing the evolution of our outcomes for the entire sample between Lima and the next largest metropolitan area in Peru, which is Arequipa. Figure 14 shows the results. We see generally similar effects to the SCM exercise. In table A.13 in the Appendix, we show the results of our estimations, for the complete sample as well as by
Just as in our SCM estimations, we do not see any effects on employment, hours, or income. In terms of occupational distribution, we see reductions in professional, blue-collar, and white-collar jobs and an increase in unskilled jobs, though the most significant effect is seen for the latter.

We show the results for the difference-in-difference between Lima and the unweighted aggregate of all the metropolitan areas in the donor pool in Table A.4.
Figure 14 Difference in difference: Lima versus Arequipa.  
Source: Own calculations based on INEI (2019b).  
Notes: Each sub-figure shows the outcome variable for Arequipa (solid line) and Lima (dashed line) in the period 2013–2019. Migration starts first semester of 2017 (vertical line).
5.5 INTERNAL MIGRATION

As suggested by Card (1990) for the Mariel Boatlift, a possible reaction of the labor market in Lima to migration from abroad was domestic migration to other areas of the country. To explore this possibility, we compare the population growth of Lima versus other metropolitan areas. In particular, we compare the change in the population of Peruvians between 18 and 75 years old in both locations in 2013 (four years prior to the shock), 2016 (the year before the shock), and 2019 (the last year in our sample).

Table 8 suggests overall lower local population growth in Lima than other metropolitan areas during the period of migration. The population growth rate in Lima between 2016 and 2019 was 2% for men and 1.6% for women. For the other metropolitan areas combined, population growth rate was substantially larger: 5.4% and 7.7%, respectively. When we see the differences by age, the results are even more striking. In both groups, there is a clear aging of the native population. However, in Lima the Peruvian population age 18 to 40 decreased by 4.6% after the influx of Venezuelans, while in the other metropolitan areas it increased by 0.5%. To check whether these trends were already happening pre-migration (and unlikely to be an effect of the migration), we also compare the population growth rate between 2013 and 2016, just prior to the period of migration. Between 2013 and 2016 the population changes are completely different from the 2016–2019 period, suggesting substantial growth in the population in Lima and negative population growth in the other metropolitan areas. A simple difference in difference estimator produces an impact of the migration to reduce the population in Lima by 10.9% for men and 14% for women, 17% for individuals 18 to 40 and 8% individuals 41 to 75. Overall, these trends are consistent with the migration shock reducing migration of native individuals (particularly the young) to Lima, and/or inducing domestic migration from Lima to other urban areas.

### Table 8

<table>
<thead>
<tr>
<th>BY GENDER</th>
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<th>OTHER MA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MEN</td>
<td>WOMEN</td>
</tr>
<tr>
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</tr>
<tr>
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<td>3,603,489</td>
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<tr>
<td>2019</td>
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<td>3,661,589</td>
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</table>

<table>
<thead>
<tr>
<th>BY AGE</th>
<th>LIMA</th>
<th>OTHER MA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>18 ≤ AGE ≤ 40</td>
<td>41 ≤ AGE ≤ 75</td>
</tr>
<tr>
<td></td>
<td>18 ≤ AGE ≤ 40</td>
<td>41 ≤ AGE ≤ 75</td>
</tr>
<tr>
<td>2013</td>
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<tr>
<td>2016</td>
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<td>3,300,893</td>
</tr>
<tr>
<td>2019</td>
<td>3,430,936</td>
<td>3,592,989</td>
</tr>
</tbody>
</table>

Venezuelan migrants might also, after arrival, engage in internal migration. While Section 2 demonstrated that most migrants to Peru arrive to Lima, it is possible they might migrate elsewhere in an endogenous manner. We shed some light on this question by analyzing the two rounds of the main available data on the locations of Venezuelans living in Peru, the Encuesta Dirigida a la Población Venezolana que Reside en el País (ENPOVE). This survey of Venezuelans living in Peru was carried out by the National Institute of Statistics (INEI) in December of 2018 and 2022. The ENPOVE 1 asks Venezuelan migrants in Peru if they have always lived in the same district (county) since arriving to Peru. Of those living in Lima/Callao, 85.1% of Venezuelan migrants interviewed who were currently living in Lima reported that since arriving to Peru, they had always lived in the current district, implying the large majority since arriving to Lima have continued to remain in Lima. Unfortunately this same information is not available in the ENPOVE2 living in Lima. However, both ENPOVE rounds ask about the year of arrival to Peru so that we can compare the

Source: Own calculations based on INEI (2019b) using population weights.
geographical location of migrants by date of arrival in both years. In the ENPOVE 1 (carried out in 2018), for those migrants reporting arriving in 2017 or 2018, approximately 58.4% are residing in Lima. In the ENPOVE2 (carried out in 2022) for those migrants reporting arriving in 2017 or 2018, approximately 56.3% are currently residing in Lima, implying that for Venezuelan migrants arriving in Lima in 2017/2018, nearly all continued to reside in Lima in 2022. We conclude that there was little internal migration of Venezuelans to other parts of Peru after settling in Lima.

6 FINAL REMARKS

The recent exodus from Venezuela to Peru was an unusual episode both in its magnitude and its suddenness. It was also heavily concentrated in the city of Lima, which allows the use of other metropolitan areas of the country as a control to estimate its effects on the labor market. Thus, the episode provides an advantageous window to study the effects of mass migration.

Our estimation exercises reveal relatively small effects on total employment, hours worked and labor income per hour. We see, however, larger adjustments in the occupational structure of the local labor force, with increases in unskilled jobs, both for men and women. These adjustments are consistent with an assignment model of the labor market, in line with, for example, Acemoglu and Autor (2011), given the fact that migrants were relatively more educated than the local labor force.

The economic literature on migration has focused, for the most part, on the adjustment of migrants to the host labor market, including the possible “downgrading” of the migrants’ skills, and on the wage impact of migration for the local labor force. Less attention has been given to reallocation of the local labor force to the changing conditions, with the exception of domestic migration. Perhaps this is due to observational conditions; in episodes in which migration was a smaller share of the labor market, or was a longer process, the adjustment of the local labor force may have been more subtle and protracted.

More generally, our paper provides some evidence that sector adjustment of the local labor force is a consequence of migration. The direction of this adjustment, of course, depends on the skills of the migrants versus those of the local population, and cultural and legal barriers to the absorption of the migrant labor force, which depend on the circumstances of each episode.

We close by noting that a relatively flexible job market, in which jobs are not rigidly linked to education levels for cultural or legal reasons, may help reduce or eliminate the distributional impact of migration. At the time of the Venezuelan migration, the flexibility and openness of the Lima labor market might be seen as helping to mitigate a humanitarian disaster with relatively low costs to local workers.

ADDITIONAL FILE

The additional file for this article can be found as follows:

- **Appendix.** Tables and Figures. DOI: https://doi.org/10.31389/eco.436.s1

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COMPETING INTERESTS

The authors have no competing interests to declare.
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