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Economic Consequences of Mass Migration: the Venezuelan Exodus in Peru

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Abstract

We study the effects of mass migration from Venezuela on Peruvian labor markets. In 2017–2018, about 870,000 Venezuelans migrated to Peru; about 84% settled in the Lima metropolitan area, where the percentage of Venezuelans in the working age population went from nil to over 10%. Migrants were more educated in average than the local labor force, and did nor face large cultural barriers. We propose a simple assignment model of the labor market, which suggests that migration will lead to a reallocation of local workers toward lower skill jobs. Using synthetic control methods, and comparing Lima with a group of other Peruvian cities, we find evidence of adjustment in occupational structure in the direction predicted by the model. Overall, market adjustment to a large shock in labor supply was strikingly smooth.

1 Introduction

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

Between 2015 and 2020, over five million people have left Venezuela as a result of the political, economic, and humanitarian crisis in the country. The largest recipient countries of Venezuelan migrants have been Colombia and Peru. In Peru, in particular, there were about 10,000 Venezuelans in late 2016 but over 870,000 by the end of 2019. As a consequence of migration, the number of people joining the labor force in Peru approximately doubled in 2018 in relation to normal years (Asencios and Castellares, 2020). Moreover, more than 60% of migrants over 15 has more than high school education, and 30% completed college, versus 43% and 16% respectively for the local population of Lima-Callao 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 implication of the model is that the effect of the migration will be a reallocation of a fraction of the local labor force toward blue collar and elementary jobs.

To study empirically the consequences of migration, we take advantage of the fact that about 84% of all Venezuelan migrants settled in the Lima metropolitan area, comprising Lima (the capital city) and the adjacent port of Callao. We construct a synthetic control for Lima using monthly data from the period 2013–2019 from Peru's largest metropolitan areas. We then use the control to 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.

We find small or negligible effects on employment or hours worked. We find, instead, evidence of adjustments in the occupational structure, with increases in elementary jobs and blue collar work for local workers. That is, consistent with the model, migrants seem to have displaced 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 than in other cities during the period migrants arrive, suggesting domestic out migration from Lima in response to the shock. Overall, it is striking that such a large shock to the labor supply was so quickly absorbed, indicating the absence of important binding rigidities in the labor market.

The literature on the economic effects of migration has often relied implicitly or explicitly 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 general equilibrium work on the effects of migration, we focus on the possibility that local workers may transit at the margin between different job types. In our model, which relates to recent assignment models of 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.[1] 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.

Interest in studying mass migration episodes linked to humanitarian disasters was sparked by the Mariel boatlift episode of 1980.[2] Because they are (in principle) sudden, unexpected shocks, migrations linked to humanitarian disasters provide a window to understand the effects of migration for local workers, and an opportunity to witness in fast motion the adjustment process in labor markets in reaction to supply shocks. In a seminal and influential 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. There is some evidence that an adjustment mechanism was the slowing down of migration to Miami from elsewhere within the United States.[3]

Recently, Peri and Yasenov (2019) revisit the labor market effects of the Mariel boatlift using synthetic control methods to choose a control group of cities that matches Miami's labor market trends and providing a disaggregated analysis in terms of skills, age, ethnicity, and gender. They focus on low-skilled workers as seems appropriate given the characteristics of migrants, and find no significant difference in the wages of high-school drop-outs in Miami relative to the city's control group after 1980, and no consistent evidence of a short-term or long-term decrease in low-skilled labor demand.[4][5]

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[1] 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.

[2] 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.

[3] Lewis (2004) provide some evidence that the production technology adjusted to the mix of workers as well.

[4] 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).

[5] See also Peri et al. (2020) for another application of synthetic control methods.

Like Peri and Yasenov (2019), we use synthetic control methods to do inferences about the effect of a mass migration episode. The episode we study has two distinguishing features, however, which add interest. First, it was arguably a 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, thus possibly leading to a different market adjustment.

Among related work, Santamaria (2020) studies the impact of Venezuelan migration to Colombia using a version of the synthetic control method. A difficulty for the identification of effects is that Venezuelan migration to Colombia started earlier, and was geographically more diffused. To find the location of migrants, Santamaria (2020) use 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. It is worth noting that Venezuelan migration to Colombia was perhaps less unanticipated, given prior waves, than to Peru, and that migrants were of similar educational levels than the local labor force so that market adjustment was potentially different.[6]

Among previous work on the Venezuelan migration to Peru, Asencios and Castellares (2020) study the effects of the migration on the labor market of Lima, using survey data for 2016–2018 to run a before-after linear probability model and a Heckman selection model. They find a reduction of 10 to 15% in employment for women aged 14–24 years with low education levels and for workers between 25 and 39 years old with incomplete tertiary or lower educational levels, in comparison to men aged 55 or older with a college degree. They also find a reduction in hourly income for high school dropouts aged 14–24 years, and for those over 54. The effects are small, and are consistent with our estimates.[7]

[6] 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.

[7] In a different vein, Morales and Pierola (2020) attempts to use spatial variation in the settle-

Other episodes of mass migration that have received attention in recent literature include out migration from Soviet Union and the former GDR to Germany and Israel (De New and Zimmermann, 1994; D'Amuri et al., 2010; Friedberg, 2001; Cohen-Goldner and Paserman, 2006), Syrian refugees in Jordan and Turkey (Fallah et al., 2019; Del Carpio and Wagner, 2015; Altindag et al., 2020), and Nicaraguan refugees in Costa Rica (Gindling, 2009). Overall, as pointed out by Clemens and Hunt (2019, pg. 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."[8]

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 synthetic control strategy. In Section 5 we present the results. In Section 6 we gather concluding remarks.

2 Venezuelan exodus in Peru

Approximately 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 host countries are Colombia, Peru, Ecuador, and Chile, with recent Venezuelan migrants constituting between 2 and 3% of the local population in each case (see Table 1). Migration to these countries has been facilitated by the commonality of language and relatively open door policies.

Before 2017 there were only about 10,000 Venezuelans in Peru. From 2017 to 2019 nearly 870,000 Venezuelans arrived to the country.[9] About 84.5% arrived by

ment of Venezuelan migrants in Peru to estimate the labor market effects of migration. This is made difficult by the fact that there is negligible to nil numbers of migrants in most Peruvian provinces, especially in rural circumscriptions.

[8] See Hanson (2009) for a general review of the empirical literature on the impact of migration on welfare.

[9] By 2020, according to R4V (2020), the number of Venezuelan migrants and refugees in Peru

Table 1: Venezuelan migrants 2016–2019

Country	Venezuelan migrants	Population (Million)	Share (%)
Colombia	1,400,000	50.3	2.75
Peru	870,000	32.5	2.63
Ecuador	385,000	17.4	2.19
Chile	371,000	19.0	1.94
United States	351,000	329.0	0.01
Brazil	224,000	211.0	0.11
Argentina	145,000	44.8	0.32
Panama	94,000	4.2	2.19

Sources: migrants from The World Bank (2019a) (using data from UNHRC R4V corresponding to November 2019), and population from United Nations, for top eight host countries.

bus covering 4,500 km in a trajectory that takes at least a few days. According to survey data (INEI, 2019c), the migrants are mainly young and come from urban areas. About 42% 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 come with their families; there are about of 117,000 infants among the migrants.

Since 2017, the Peruvian government have implemented a temporary residence permit program ("permiso temporal de permanencia" or PTP for its slightly oxymoronic name in Spanish) to address the immigrant crisis, influenced by a similar program in Colombia. The PTP allows migrants to reside in the country, 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, 2019c).

Venezuelans settled mostly in the coastal area of the 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

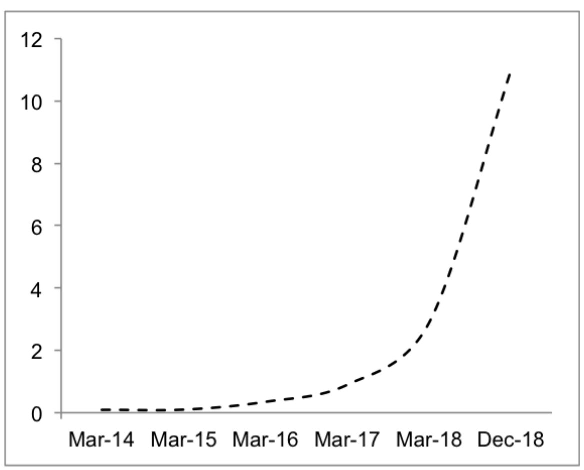
reached 1,100,000.

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

Department	% share of Venezuelan migrants	% share of Department population
Lima	78.0	6.7
La Libertad (Trujillo)	3.9	2.1
Arequipa	3.0	0.7
Lambayeque (Chiclayo)	1.2	0.7
Callao	5.8	0.6
Piura	1.4	0.3
Ancash (Chimbote)	1.3	0.4
Cusco	0.5	0.3
Ica	1.6	0.4
Tacna	0.5	1.1
Tumbes	0.5	1.5
Junin (Huancayo)	0.3	0.2

Notes: The most populous city in parenthesis when it is not a namesake. Callao province is administratively treated as a Department. The Department of Lima includes other (much less populated) provinces than Lima. Sources: The World Bank 2019b and Bacigalupo and Goldstein 2019.

Figure 1: Venezuelan migrants as percentage of Lima's labor force



Source: Asencios and Castellares (2020).

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

	Venezuelan migrants	Lima and Callao	Peru
Basic or no schooling		1.5	5.1
Primary school	10.2	10.3	19.1
High school	31.9	45.1	42.3
Vocational school	19.2	18.2	14.2
Some college	13.0	8.9	6.6
College (complete)	25.7	13.6	11.1
Graduate studies	0.7	2.3	1.5

Sources: INEI (2019c) for Venezuelan migrants to Peru (15 years and older) and INEI (2019a) for Lima and Callao provinces and for Peru (14 years and older).

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 have each one tenth of the population of Lima and account for 4% and 7% of GDP respectively. Thus, migrants settled more than proportionally in Lima in relation to population and economic activity. Absent previous migrant networks, Lima was an obvious destination for recent arrivals.[10] By December 2018, Venezuelan migrants were about 10% of the population above 18 working or looking for a job in metropolitan Lima (Asencios and Castellares (2020); see figure).

Working age migrants are in average more educated than the local population in the Lima metropolitan area and in Peru at large (see Table 3). About 58% of the 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-Callao, and 34% and 19% for Peru.

According to survey data (INEI, 2019c), the vast majority of working age migrant inserted themselves in the Peruvian labor market: the occupation rate of migrants

[10] 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).

Table 4: Employment of Venezuelan migrants (%) and Peruvians

	Venezuelan migrants	Peruvians
Elementary	35	27
Machinery, transportation	7	9
Construction, energy, telecomm	14	11
Agribusiness, fisheries	0	5
Services, sales	30	21
Technicians	7	9
Office and admin	6	8
Professionals	2	10

Note: Urban population for Peru. Source: The World Bank (2019b), using INEI (2019b) and INEI (2019c).

is 90% compared to 70% of Peruvians. The unemployment rate for migrants is 6%, very similar to the rate of locals—and very different from Colombia, where Venezuelans have an unemployment rate of 22%. About half got employed in the hotels, restaurants, and retail industries, where hiring is more flexible, since about 84% of the total employment in these industries is informal (The World Bank, 2019b).

Table 4 details the occupations of Venezuelan migrants in comparison with those of the Peruvian urban population. As in other cases of migration there some "downgrading" of the migrants' skills, in the sense of Venezuelans with high school or college studies are taking, at least temporarily, elementary jobs (The World Bank, 2019b). What is impressive, however, is that many seem to be able to find technical or administrative jobs, and about a third have found jobs in services or retail.

Given the schooling of Venezuelan migrants in relation to the local labor force, we conjecture that their integration to the job market could reduce the premium for school 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 Peruvians.

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 (say, blue collar jobs) and 2 (say, white collar jobs), and a continuum of workers of mass μ. Each worker in the economy has some skill level $s \in \Re$. Workers' skills are distributed according to some continuous probability density ϕ with support given by some interval $[\underline{s}, \overline{s}]$. 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 $x_2(s)/x_1(s)$ is continuous in s and strictly increasing for $s \in (\underline{s}, \overline{s})$. 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 $[\underline{s}, \overline{s}]$ 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 goes 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,[11] that is,

$$L_1 = \left\{ s \in [\underline{s}, \overline{s}] : \frac{x_2(s)}{x_1(s)} < \frac{w_1}{w_2} \right\} \quad \text{and} \quad L_2 = \left\{ s \in [\underline{s}, \overline{s}] : \frac{x_2(s)}{x_1(s)} \geq \frac{w_1}{w_2} \right\},$$

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

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

$$X_j(s) = \mu \int_{z \in L_j(s)} x_j(z)\phi(z)dz$$

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

$$\frac{x_2(s)}{x_1(s)} = \frac{w_1}{w_2} \quad \text{and} \quad \frac{w_1}{w_2} = \frac{F_1(X_1(s), X_2(s))}{F_2(X_1(s), X_2(s))}$$

[11] The set of workers who are indifferent has measure zero; we simply allocate them to sector 2.

which together imply

$$\frac{x_2(s)}{x_1(s)} = \frac{F_1(X_1(s), X_2(s))}{F_2(X_1(s), X_2(s))}. \tag{1}$$

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 $\underline{s}$ and arbitrarily close to zero for s close to $\overline{s}$. 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

We model migration as a shock to the labor force. In particular, let the original population of workers be of mass 1 and distribution of skills ϕ_n, and let the migrant population be of mass m and distribution of skills ϕ_m.

To analyze the impact of migration, we define

$$x(s) \equiv x_2(s)/x_1(s)$$

to be the skill ratio for the marginal worker,

$$T(X_1/X_2) \equiv F_1(X_1, X_2)/F_2(X_1, X_2)$$

to be the marginal rate of transformation between sectors, and

$$X(s, m) \equiv \frac{X_{1n}(s) + mX_{1m}(s)}{X_{2n}(s) + mX_{2m}(s)}$$

to be the ratio of effective labor, where

$$X_{jn}(s) = \int_{z \in L_j(s)} x_j(z)\phi_n(z)dz \quad \text{and} \quad X_{jm}(s) = \int_{z \in L_j(s)} x_j(z)\phi_m(z)dz$$

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

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

$$\frac{d(w_1/w_2)}{dm} = \underbrace{x'(s)\frac{ds}{dm}}_{\text{total effect}} = \underbrace{T'\partial_m X}_{\text{direct effect}} + \underbrace{\frac{(T')^2 \partial_m X \partial_s X}{x'(s) - T'\partial_s X}}_{\text{indirect effect}}. \tag{2}$$

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

$$\frac{d(X_{1n}/X_{2n})}{dm} = \partial_s(X_{1n}/X_{2n})\frac{ds}{dm}. \tag{3}$$

Near $m = 0$, we have

$$\partial_m X = \frac{X_{2m}}{X_{2n}}\left(\frac{X_{1m}}{X_{2m}} - \frac{X_{1n}}{X_{2n}}\right),$$

which is negative as long as the migrant labor force is relatively skilled compared to the local labor force, that is,

$$\frac{X_{1m}}{X_{2m}} < \frac{X_{1n}}{X_{2n}}. \tag{C}$$

We also have

$$\partial_s X = \partial_s(X_{1n}/X_{2n}) = \frac{X_{1n}}{X_{2n}}\left(\frac{x_1(s^*)}{X_{1n}} + \frac{x_2(s^*)}{X_{2n}}\right)\phi(s^*) > 0.$$

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) we get that 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,

$$\frac{d(w_1/w_2)/dm}{w_1/w_2} \approx \left(\frac{X_{1m}}{X_{1n}} - \frac{X_{2m}}{X_{2n}}\right)\Big/\sigma\ . \tag{4}$$

and

$$\frac{d(X_{1n}/X_{2n})/dm}{X_{1n}/X_{2n}} \approx 0,$$

where σ 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

$$\frac{d(w_1/w_2)/dm}{w_1/w_2} \approx 0,$$

and

$$\frac{d(X_{1n}/X_{2n})/dm}{X_{1n}/X_{2n}} \approx \frac{X_{2m}}{X_{2n}} - \frac{X_{1m}}{X_{1n}}. \tag{5}$$

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 and the local (Lima) labor force with more than high school as X_2 and the remainder as X_1 (see table 3);

Figure 2: Equilibrium salaries and employment

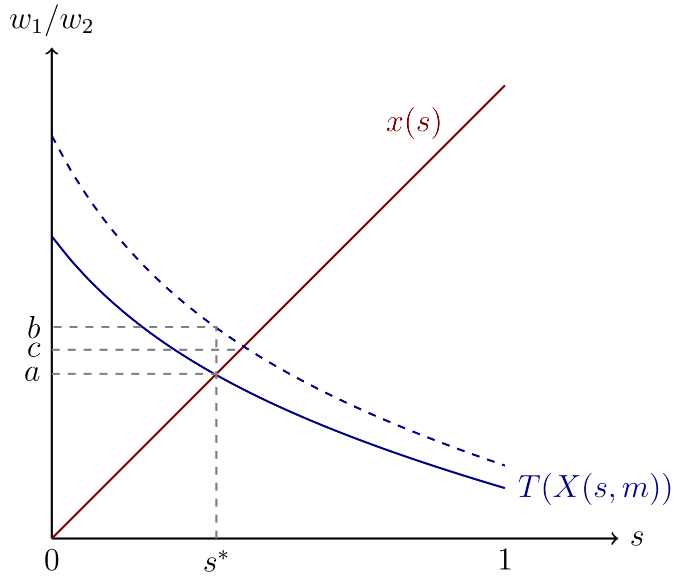
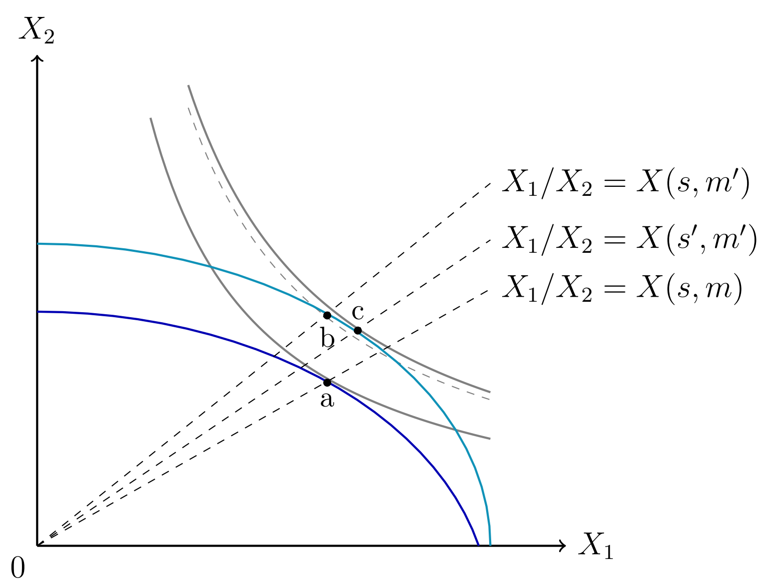


Figure 3: Equilibrium production



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 movement of about 2.6% of the local labor force from high-skilled to low-skilled jobs in response to a migration shock of 10% of the labor force.

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 $\underline{s}$ (all labor is assigned to sector 2) to $\overline{s}$ (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 ϕ 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 that appear in the database between January 2013 and December 2019. The ENAHO covers both the urban and rural areas of Peru, and is collected continuously over 12 months. It contains information for both households and individual members. For households, the ENAHO collects information regarding access to basic services, characteristics of the dwelling, household composition, as well as both income and spending patterns. For individual members, the survey contains basic socio economic information (including place of actual residence and place of birth) as well as detailed modules on education, health access and, for those over the age of 14, employment and earnings.

The survey has two sample components. The first are the cross-section households; each year the same sampling unit (consisting of around 120 household) is visited at the same time but different households are chosen. The cross-section component of the ENAHO has a yearly average of 35,000 households. The second component are panel households; each year the same sampling unit is visited at the same time and the same household is interviewed for a total of 5 consecutive years with a rotation of 20 percent per year. On a yearly average 11,000 households in the ENAHO are considered panel. Urban households make up 70 percent of the total survey.

In order to maximize the number of observations, we use the cross-section variation of the ENAHO. Since we want to understand the effect of the shock of the Venezuelan migrants on the labor market outcomes of local workers, we restrict our sample to Peruvian-born individuals. The sample includes those born between 18 and 75 years old, and exclude members of the Armed Forces. In order to compare the evolution of the labor market in the place with the highest share of migrants

(Lima-Callao) with comparable places, we keep in our sample individuals who reside in the urban areas of the largest nine metropolitan areas of Peru: Lima-Callao, Arequipa, Trujillo, Chiclayo, Piura, Iquitos, Cusco, Chimbote, and Huancayo (see figure 4). One third of Peruvians reside in Lima-Callao (almost 13 million individuals), and other metropolitan areas separately considered are much smaller; working with an aggregate of other metropolitan areas is the best available approximation.

The total sample consists of 138,013 observations, of which a little over half (51.5%) belong to Lima-Callao, and the other half is distributed in the rest of the metropolitan areas (see Table 5). In order to have information at the Metropolitan Area level, we aggregate different codes of Geographic Location (UBIGEO - the smallest territorial unit available in the ENAHO) with a semester frequency to obtain a panel of metropolitan areas. In the Appendix, tables A.1 and A.2, we show how the metropolitan areas of Peru were constructed from the ENAHO.

Table 6 shows the descriptive statistics of Lima-Callao versus the aggregation of the other metropolitan areas in our sample, before the influx of Venezuelan migrants. The labor market outcomes that we analyze are employment, hours in principal activity, informal work (defined as workers with no contribution to the pension scheme), labor income per hour,[12] 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).[13]

[12] For our estimations for this variable, we use only employed workers and exclude the lower 10% and largest 10% of the distribution to avoid working with outliers.

[13] This division of occupations corresponds to the major group titles of the the ILO's International Standard Classification of Occupations (ISCO). See: https://www.ilo.org/public/

Figure 4: Most populated Peruvian metropolitan areas

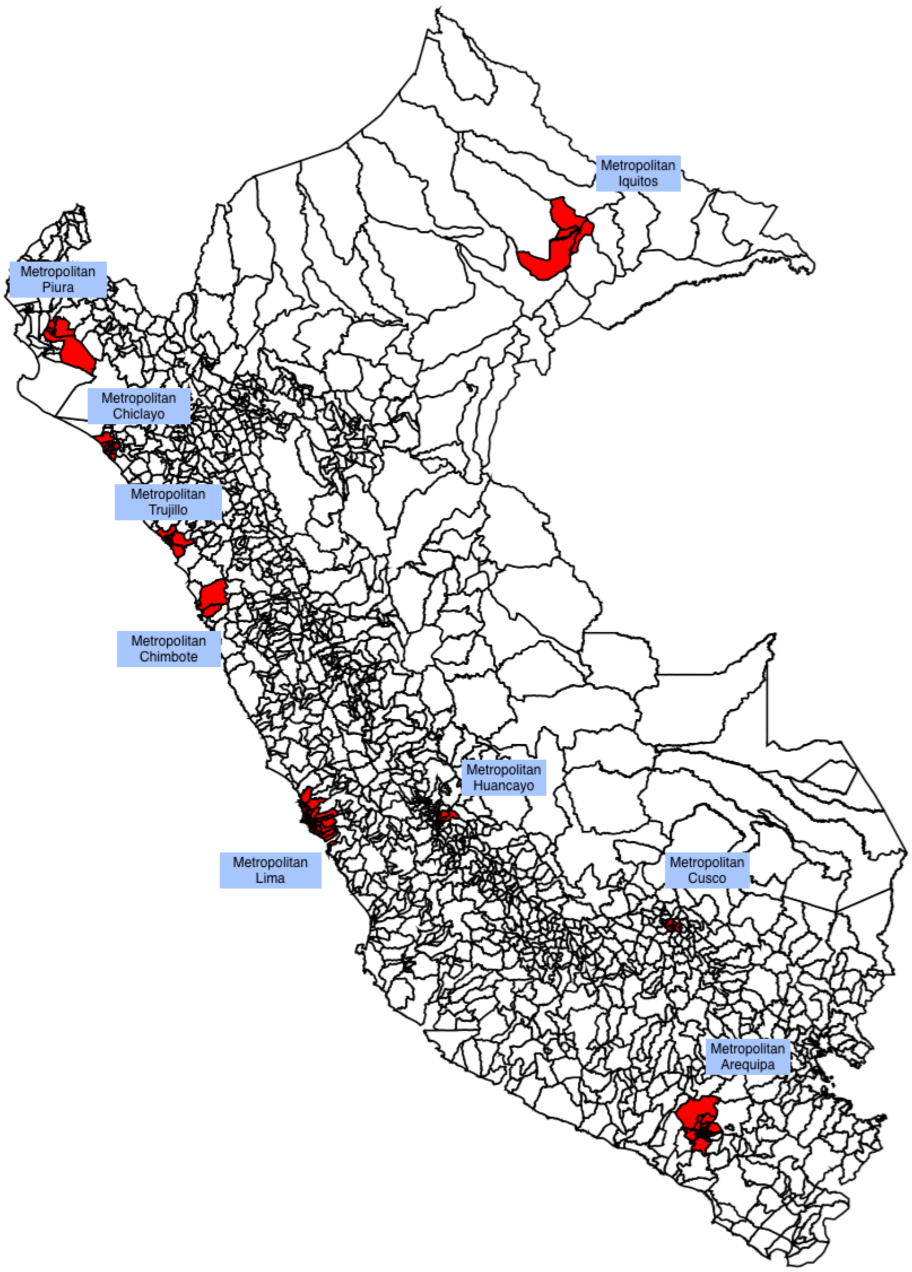


Table 5: Sample distribution

(a) by year

Year	Frequency	Share (%)
2013	19.720	14.29
2014	19.866	14.39
2015	18.787	13.61
2016	19.931	14.44
2017	20.018	14.50
2018	20.475	14.84
2019	19.216	13.92

(b) by metropolitan area (MA)

MA	Share (%)
Lima-Callao	51.51
Arequipa	9.29
Trujillo	6.50
Chiclayo	7.70
Piura	5.47
Iquitos	7.34
Cusco	3.14
Chimbote	4.82
Huancayo	4.22

Table 6: Descriptive statistics (before 2017)

	Lima-Callao		Other MA	
	Mean	SD	Mean	SD
Age	41.52	15.69	41.11	15.65
Women	0.52	0.50	0.53	0.50
Married	0.52	0.50	0.54	0.50
Household members	4.67	2.08	4.91	2.29
High school graduates	0.77	0.42	0.72	0.45
Labor force participation	0.72	0.45	0.72	0.45
Not working	0.32	0.46	0.32	0.47
Informal worker	0.36	0.48	0.43	0.50
Monthly income (Soles)	1099.00	1707.96	871.50	1325.00
Weekly hours	30.70	25.30	30.01	25.98
Professional workers	0.09	0.29	0.09	0.29
White collar workers	0.28	0.45	0.27	0.45
Blue collar workers	0.15	0.36	0.16	0.37
Unskilled workers	0.16	0.36	0.16	0.37
Sample	41,131		37,173	

As shown by table 6, Lima-Callao is similar in most outcomes to other areas before the migration shock, although the share of informal workers is smaller in Lima-Callao, and the monthly income in constant soles is higher, possibly reflecting commensurately higher living expenses. Note that 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.

4.2 Empirical strategy

Our approach is based on the Synthetic Control Method (SCM). The SCM compares the evolution of an aggregate outcome for the unit affected by the intervention to the evolution of the same outcome for some control group, using a weighted average of the set of control or "donor" units. 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 cities in the donor pool that are similar to the treatment unit in terms of covariates that are predictive of post-intervention outcomes and pre-intervention outcome values. The counterfactual, called the "synthetic unit," serves to outline what would have happened to the aggregate treated unit had the treatment never occurred. Unlike comparative case studies, the SCM allows to make statistical inferences. Unlike to the traditional difference-in-difference approach with one treated unit, it allows to derive robust and conservative test statistics (the difference-in-difference approach will tend to lack power) and constructs a counterfactual similar to the treated unit prior to the shock (Billy and Packard, 2020).

Following Abadie and Gardeazabal (2003), Abadie et al. (2010), Abadie et al.

english/bureau/stat/isco/isco88/major.htm.

(2015), and Peri and Yasenov (2019), we consider 9 metropolitan areas indexed by $j = 0, 1, 2, \ldots, 8$ and denote Lima-Callao as 0, while we call the group of all the rest the "donor pool." We define a vector G_0 of dimension $k \times 1$ whose elements are equal to the values of variables that help predict our outcomes in Lima-Callao between the first semester of 2013 and the second semester of 2016, before the influx of Venezuelan migrants. Furthermore, we define a $k \times 8$ matrix, 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 $W^* = (w_1, \ldots, w_J)$ that produces a convex combination of variables in cities in the donor pool, G, to approximate as close as possible, in terms of a quadratic error, the pre-treatment vector of variables chosen for Lima-Callao, G_0.[14] In other words, 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-Callao and synthetic Lima-Callao, made up of all the other metropolitan areas. We minimize the distance for the outcome under analysis, share of high school graduates, average age, share of unskilled workers, share of retail workers, and unemployment rate.

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:

$$y_{it} = \alpha + \beta_1 Age_{it} + \beta_2 Men_{it} + \beta_3 Edu_{it} + \delta_t + \gamma_1(Age_{it} \times \delta_t) + \gamma_2(Men_{it} \times \delta_t) + \gamma_3(Edu_{it} \times \delta_t) + \epsilon_{it}, \quad (6)$$

where Age_{it} is a dummy that takes the value of 1 for individuals older than 41 (the median age); Men_{it} takes the value of 1 for men; Edu_{it} is a dummy for those with

[14] W^* is chosen to minimize $G_0 - GW$, that is $W^* = \arg\min(G_0 - GW)'V(G_0 - G_J W)$ subject to $\sum_{j=1}^{J} w_j = 1$ and $w_j \geq 0$. The weighting matrix V is chosen to minimize the mean squared predicted error of the outcome before the migrant influx, that is $V^* = \arg\min(1/T_0)\sum_{\underline{t}}^{\bar{t}}(Y_{0,\bar{t}} - \hat{Y}_t(V))^2$, where $\underline{t}$ is the first semester of 2013, $\bar{t}$ is the second semester of 2016, the period before the influx, and $\hat{Y}_t = \sum_{j=1}^{J} w_j Y_{j,t}$ where $w_j \geq 0$ and $\sum_{j=1}^{J} w_j = 1$.

more than high school education, and δ_t are a series of two-semester dummies. This produces, for each outcome under analysis, a residual ϵ_{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.

5 Results

5.1 Main results

To construct the synthetic Lima-Callao, we match labor market outcomes' correlates at the metropolitan area level prior to the first semester of 2017, when the influx of Venezuelan started increasing. These correlates include share of high school graduates, unemployment rates, share of individuals who are employed in the unskilled sector, share of individuals employed as service workers and shop and market sales workers, and the share of individuals between 18 and 35 years old. Additionally, for each outcome analyzed, we include as control the evolution of such outcome prior to 2017.

To determine the quality of matches between Lima-Callao and its synthetic control, we can do both a visual inspection as well as compare the balance among predictors between the two units. As can be seen in figure 5, prior to the Venezuelan migration, the two trends overlap for the outcomes analyzed—which is expected for the SCM to be a good match. Our predictors suitably match Lima-Callao to the counterfactual.[15] Predictor balance in Table A.3 in the Appendix suggest synthetic Lima-Callao tracks well with the real one.

Figure 5 captures outcome variables for Lima-Callao and its synthetic control for labor market measures in our sample. After the first semester of 2017, the outcome

[15] Our estimations do a good match for all variables except for informality, and therefore we are not able to make conclusions about this variable.

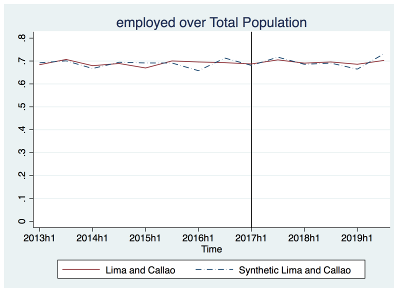
trends for employment, hours in principal activities, informality, do not separate from their synthetic control. There seems to be no effect of the influx of Venezuelans in those variables—though, as previously said, SCM might not be doing a good match for informality. In terms of labor income per hour, we see an initial negative effect on those employees in Lima-Callao, but such effect dissipates in 2018.

In terms of the structure of employment, we see little change for the share of profesional jobs, and a separation of trends between treatment and synthetic control for the shares of white collar jobs, blue collar jobs and, particularly, unskilled jobs. For the latter three variables, the outcome trends overlap for the first two semesters after the influx of Venezuelans, but then start separating: there is a decrease in white collar jobs and blue collar jobs in Lima-Callao, and an increase in unskilled jobs. The differences seem to grow over time.

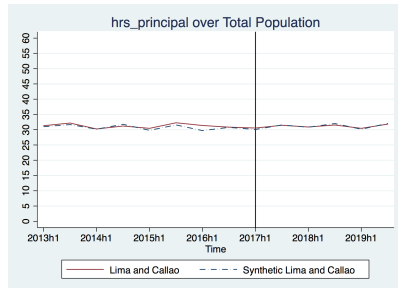
Ascertaining a point for a 'before' and 'after' migration to analyze quantitatively the effects on employment is tricky even for a sudden event like this; see figure 2. If we consider the change in unskilled jobs from the second semester of 2018 to the second semester of 2019, the change is about 3 percent points, near the 2.226 percent points for that period according to the difference in differences estimation in table A.9. This is in the ballpark of the upper bound found from the model in the absence of significant movements in relative salaries.

In figure 6(a) we report the ratio of salaries in professional, white collar and blue collar jobs in relation to unskilled jobs, using the average for salary earners ("asalariados"). In figure 6(b) we report the ratio 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 some jobs classified as blue collar or white collar can be performed with little formal education and would be closer the theoretical definition of unskilled. Though the match is not very good before migration, salaries in Lima-Callao seem to exhibit either a constant or decreasing gap in relation to salaries for synthetic Lima.

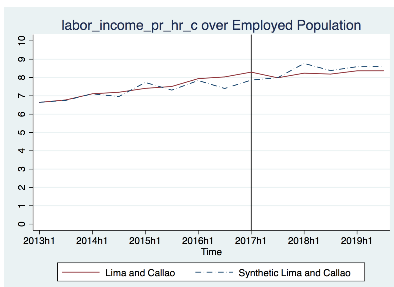
Figure 5: Complete sample results



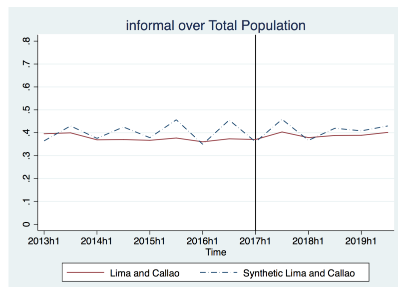
(a) Employment



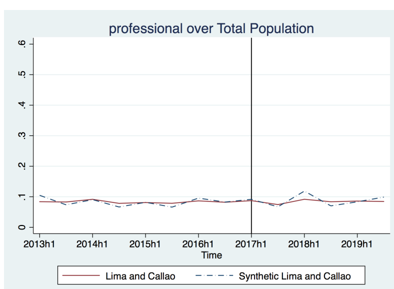
(b) Hours



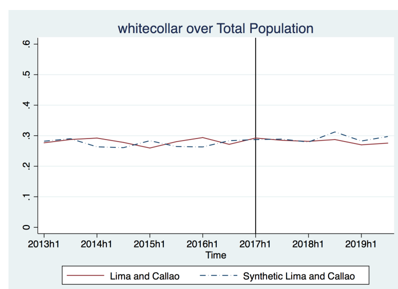
(c) Labor income per hour (for those employed)



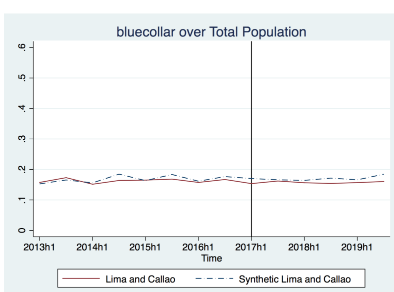
(d) Informality



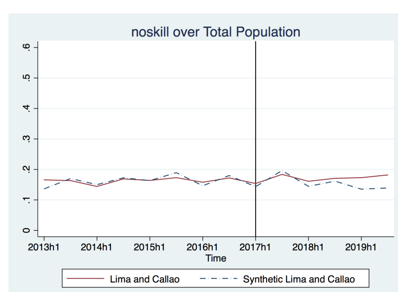
(e) Professional jobs



(f) White collar jobs



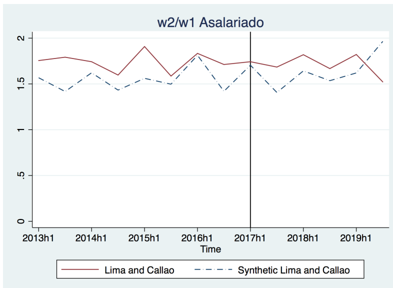
(g) Blue collar jobs



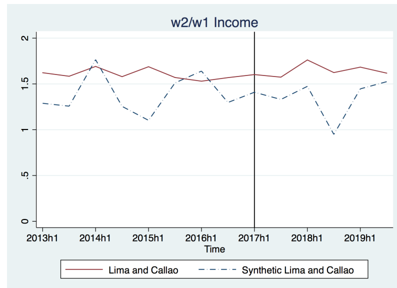
(h) Unskilled jobs

Donor weights (%): (a) Are (74.1), Chim (25.4), Hua (0.4); (b) Are (59.1), Chic (4.9), Piu (16.2), Hua (19.8); (c) Are (96.1); Chim (3.9); (d) Are (100); (e) Are (77.2), Chic (4.9), Chim (16.5), Hua (1.4); (f) Are (46.5), Piu (19.4), Hua (34.1); (g) Are (46.1), Chic (0.3), Piu (24.3), Hua (29.3); (h) Are (71.9), Tru (6.1), Chim (22.1).

Figure 6: Skilled vs unskilled salaries and earnings



(a) Salaries



(b) Average earnings

We conclude then that the influx of Venezuelans did not imply changes in employment or hours work, just a small and brief negative effect on income, and little or no effect on relative salaries, but it did create changes in the structure of the Peruvian labor market by shifting workers from white or blue-collar jobs to unskilled ones.

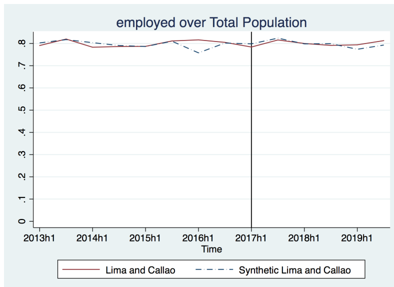
5.2 Results by gender

Figures 7 and 8 captures outcome variables for Lima-Callao and its synthetic control for both all of our labor market measures in our sample, for men and women respectively. In both samples, it can be seen that prior to the influx of Venezuelan migrants, the trends for Lima-Callao and its counterfactual track closely with each other.[16] Tables A.4 and A.5 in the Appendix show the predictor balance. Figure 7 shows that for Peruvian men in Lima-Callao, the increase in Venezuelans in the labor market did not imply any changes in employment, hours, share of professional jobs, or share of white collar jobs. It did however seem to have caused a decrease in the share of blue collar jobs, and an increase in unskilled ones. Moreover, there seems to be a small decrease in labor income per hour, though such differences decreases over time (while the difference in occupations seem to grow over time).

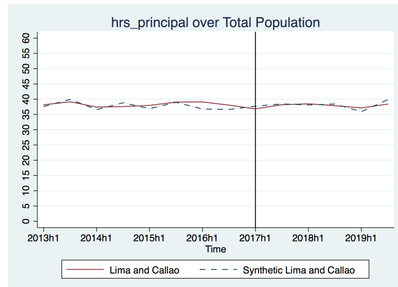
Figure 8 shows the effects for women. In this case, the change in occupations for

[16] Once again, we see that for informality the SCM is not doing a good job in producing the match.

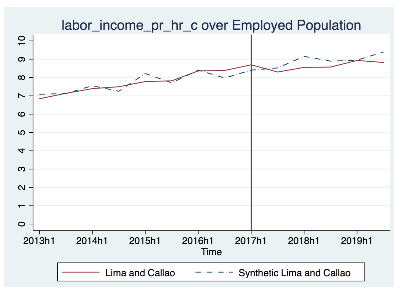
Figure 7: Sample results for men



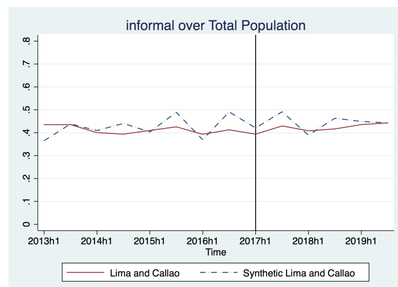
(a) Employment



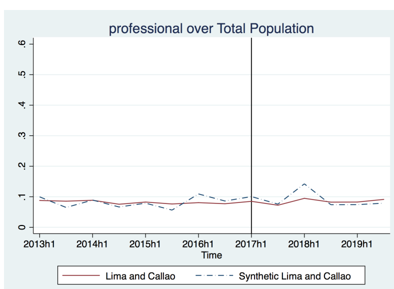
(b) Hours



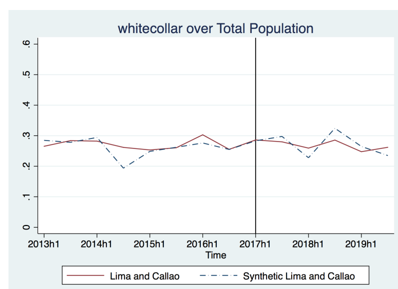
(c) Labor income per hour (for those employed)



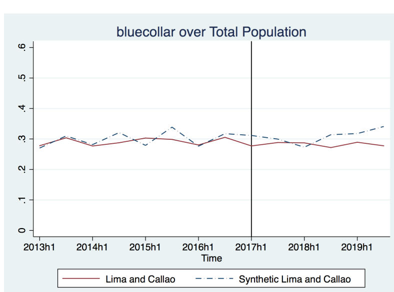
(d) Informality



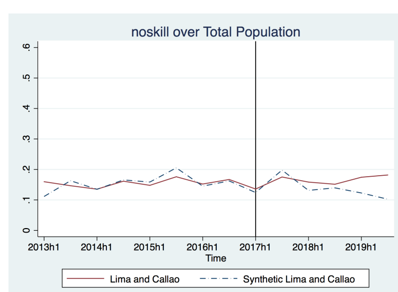
(e) Professional jobs



(f) White collar jobs



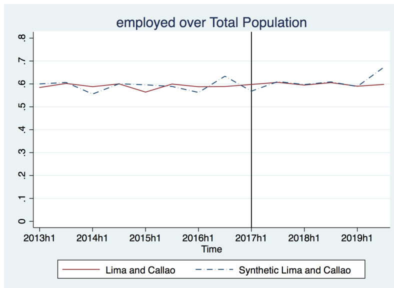
(g) Blue collar jobs



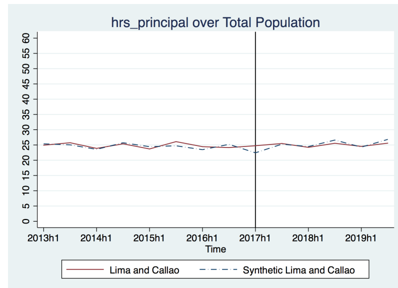
(h) Unskilled jobs

Donor weights (%): (a) Are (63.0), Tru (37.0); (b) Are (67.6), Chic (24.2), Piu (5.2), Hua (3.0); (c) Are (75.5), Tru (10.8), Chic (12.2), Hua (1.4) ; (d) Are (100.0); (e) Are (77.6), Chic (3.0), Chim (17.8), Hua (1.6); (f) Are (3.4), Piu (38.8), Hua (57.8); (g) Are (56.7), Chic (7.4), Piu (12.9), Hua (23.0); (h) Are (80.1), Tru (19.9).

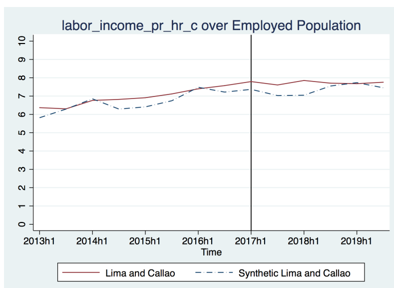
Figure 8: Sample results for women



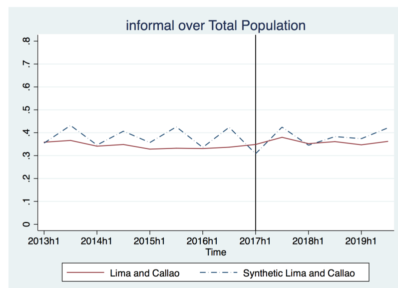
(a) Employment



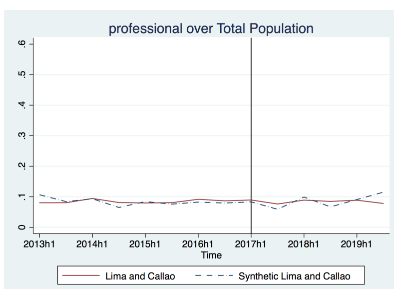
(b) Hours



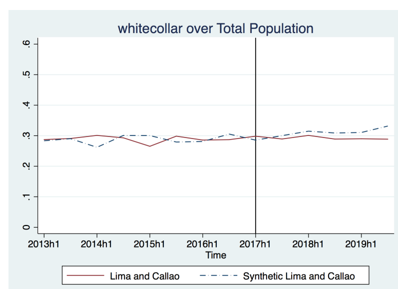
(c) Labor income per hour (for those employed)



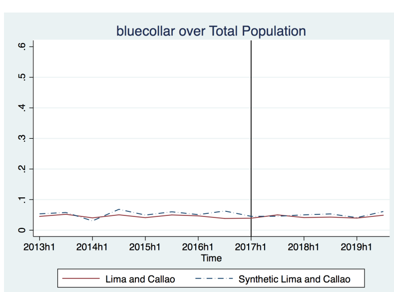
(d) Informality



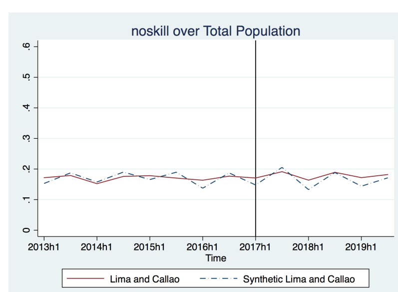
(e) Professional jobs



(f) White collar jobs



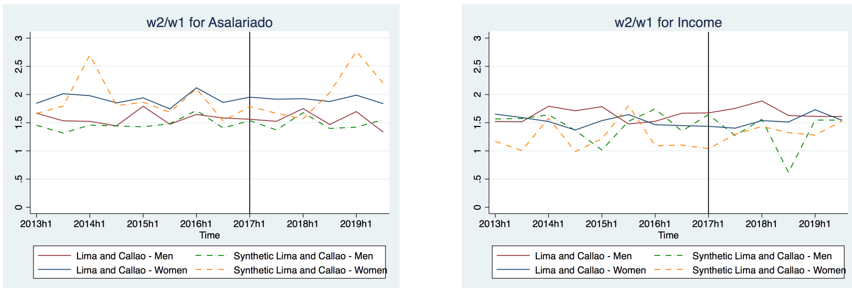
(g) Blue collar jobs



(h) Unskilled jobs

Donor weights (%): (a) Are (67.1), Tru (10.7), Chic (8.5), Chim (13.7); (b) Are (79.4), Tru (13.5), Chic (4.3), Hua (2.8); (c) Tru (28.5), Cus (36.2), Hua (35.3); (d) Are (84.9), Chic (15.1); (e) Are (75.2), Tru (6.7), Chic (4.9), Chim (11.8), Hua (1.3); (f) Are (83.6), Tru (15.9), Chic (0.5); (g) Are (56.4), Chic (20.2), Piu (23.3); (h) Are (77.0), Tru (21.2), Chic (1.8).

Figure 9: Skilled vs unskilled salaries and earnings by gender



(a) Salaries (b) Average earnings

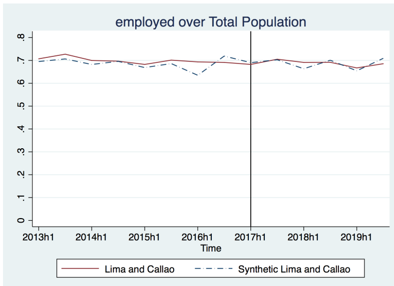
Peruvian women can be seen as a move from white-collar jobs to unskilled ones. No changes are seen for professional or blue-collar jobs, nor for hours worked. However, in the case of employment, the trends do not separate except for the last semester analyzed. Thus, there might be a non-immediate decrease in employment for women. In the case of labor income per hour, there seems to be an increase for women, which closes with time, though it is not clear if it is a product of the poor quality of the match for this outcome.

In figure 9 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 may be a negative shock for skilled salaries for women. This is consistent with a smaller adjustment in sector employment for women.

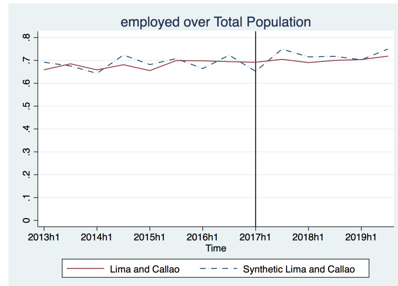
5.3 Results by age and educational level

In figures 10 and 11, we report in the ratio of employment and salaries 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).

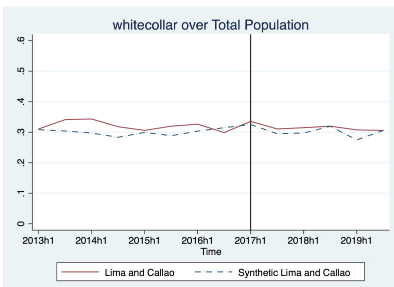
Figure 10: Occupations by age



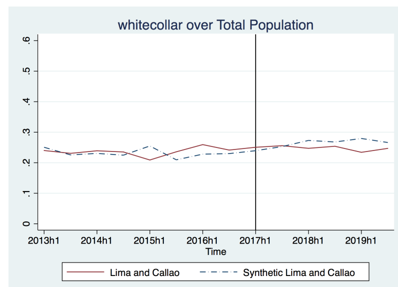
(a) Employment: 18≤age≤40



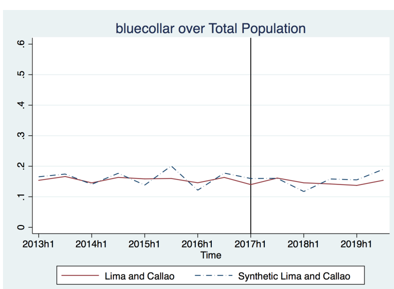
(b) Employment: 41≤age≤75



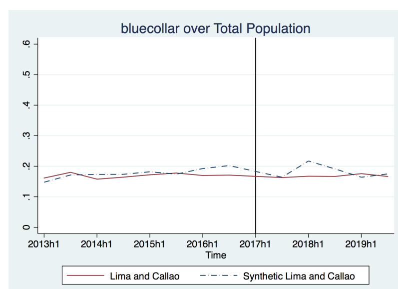
(c) White collar: 18≤age≤40



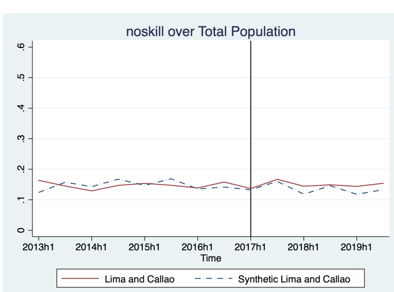
(d) White collar: 41≤age≤75



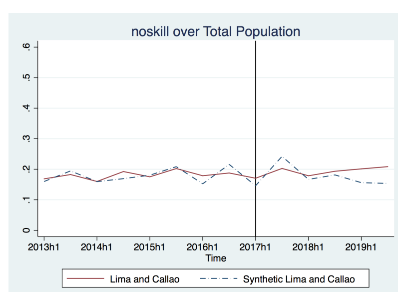
(e) Blue collar: 18≤age≤40



(f) Blue collar: 41≤age≤75

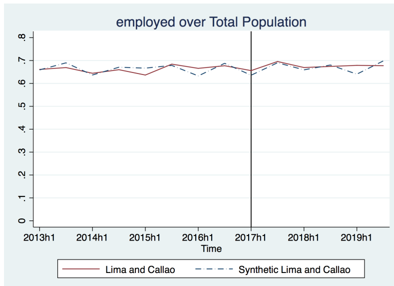


(g) Unskilled: 18≤age≤40

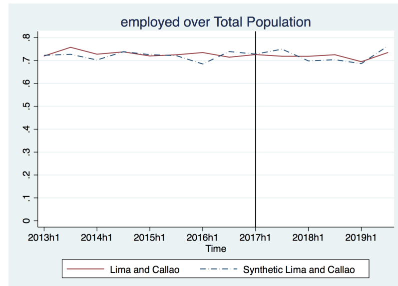


(h) Unskilled: 41≤age≤75

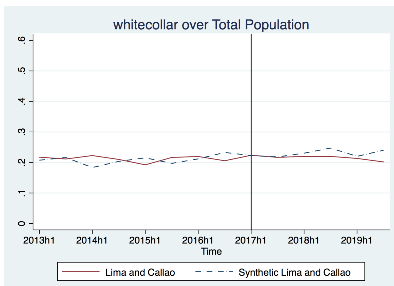
Figure 11: Occupations by education level



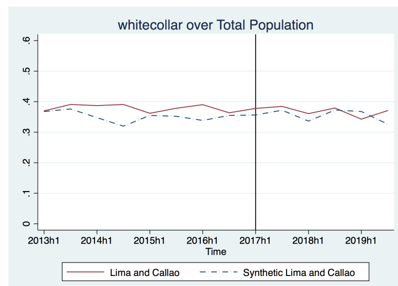
(a) Employment: low education



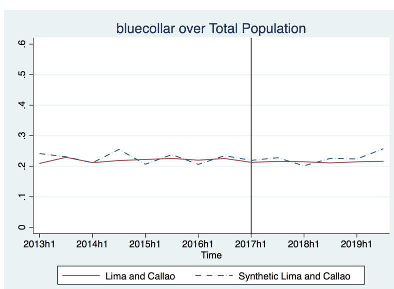
(b) Employment: high education



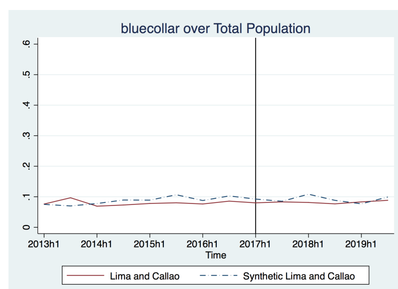
(c) White collar: low education



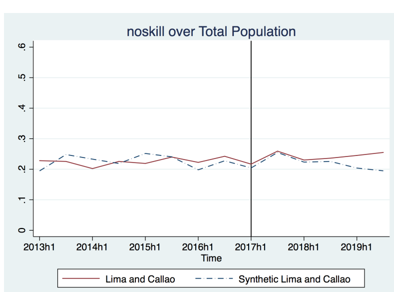
(d) White collar: high education



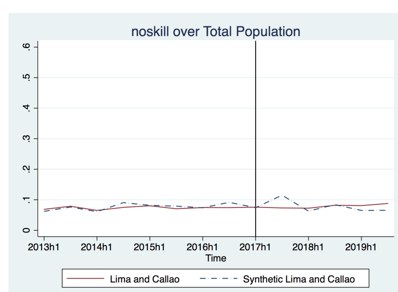
(e) Blue collar: low education



(f) Blue collar: high education



(g) Unskilled: low education



(h) Unskilled: high education

5.4 Robustness checks

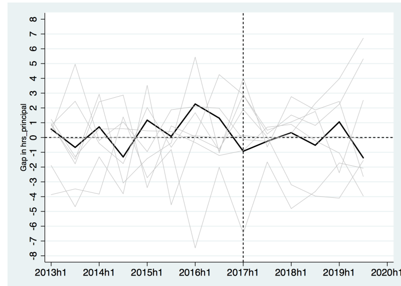
Following Abadie and Gardeazabal (2003), Abadie et al. (2010), and Peri and Yasenov (2019), we assess the significance of our results by comparing our estimated treatment effects against an estimated distribution of placebo effects. That is, we created a synthetic Arequipa, synthetic Trujillo, etc., using the other metropolitan areas as potential donors, and simulated that each of these cities were the one that had the big inflow of migrants. The grey lines in figure 12 are the placebo effects or permutations, and the dark one represent what was found before for Lima-Callao. We use this distribution to see 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 that we actually observed an effect (labor income per hour, white collar jobs, unskilled jobs and blue collar jobs), Lima-Callao lies on or near the extreme of the distribution of the simulated permutation effects. Specifically, Lima-Callao is on the upper envelope of the distribution of placebo effects for unskilled jobs. It seems improbable then that those effects would have been observed in the absence of the migrant shock. With respect to labor income per hour, we see Lima-Callao on the lower envelope of the distribution of placebo effects, particularly immediately after the shock. For blue collar jobs, we see Lima-Callao in the middle of the distribution, so it is not possible to determine if what was observed was the product of chance. In the Appendix, we repeat the exercise dividing the sample by gender, age, and educational level (see figures A.1, A.2, A.3 and A.4).

We also run a basic difference-in-difference model comparing the evolution of our outcomes for the entire sample between Lima-Callao and the next largest metropolitan area in Peru, that is Arequipa. Figure 13 shows the results. We see generally similar effects to the SCM exercise, though in the comparison between Lima-Callao and Arequipa it is clear that after the migrant shock there was a decrease in the share of blue-collar jobs and an increase in the share of unskilled ones. Note that we are not forcing the parallel trend assumption in this case, as we are doing this exercise

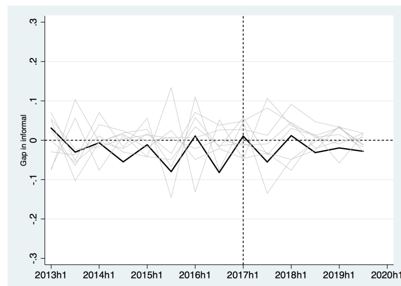
Figure 12: Simulated permutations: all sample

(a) Employment

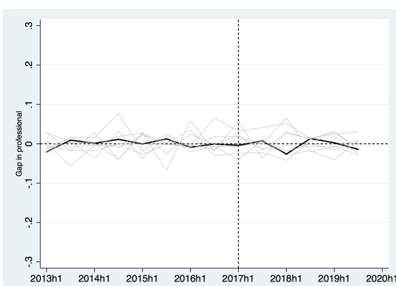


(b) Hours

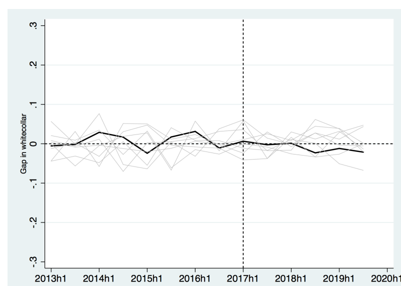
(c) Labor income per hour



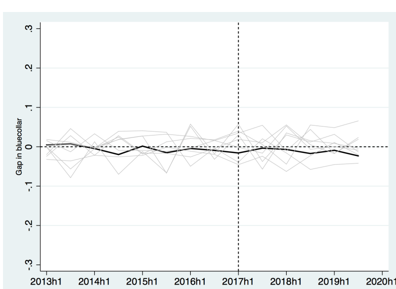
(d) Informality



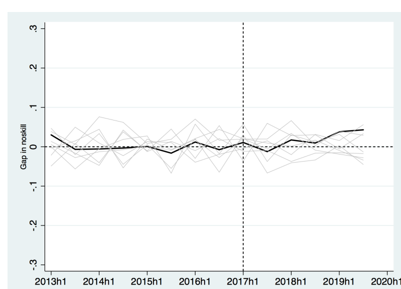
(e) Professional jobs



(f) White collar jobs

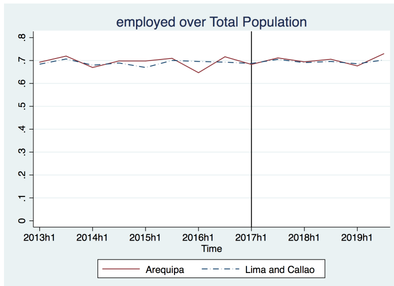


(g) Blue collar jobs

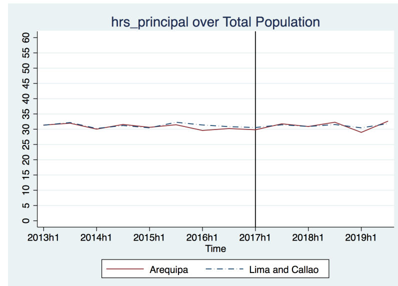


(h) Unskilled jobs

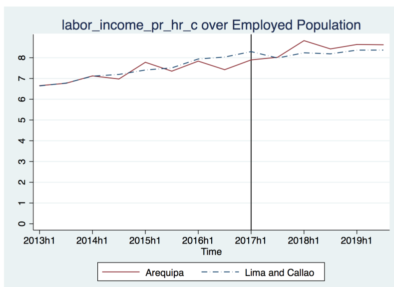
Figure 13: Difference in difference: Lima vs Arequipa



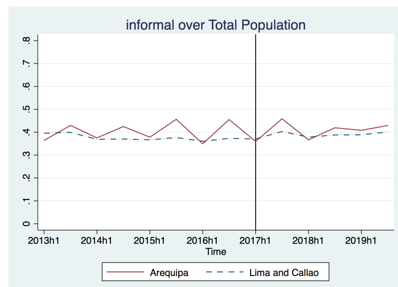
(a) Employment



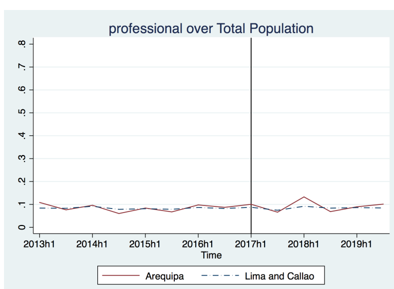
(b) Hours



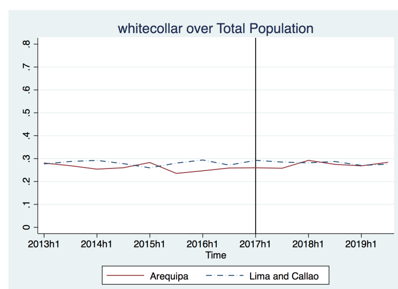
(c) Labor income per hour



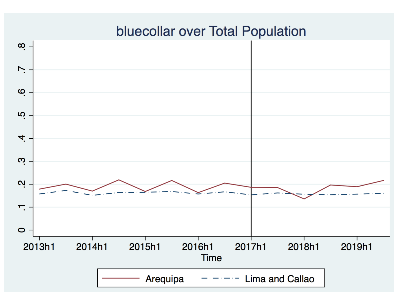
(d) Informality



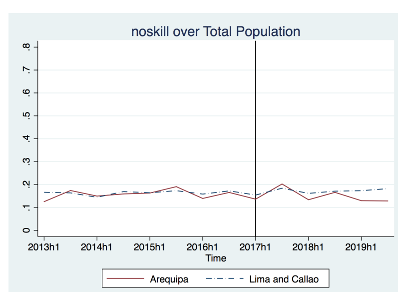
(e) Professional jobs



(f) White collar jobs



(g) Blue collar jobs



(h) Unskilled jobs

as a robustness check for our SCM findings. In table A.8 in the Appendix we show the results of our estimations, for the complete sample as well as by gender, age, and educational level.[17] Just as in our SCM estimations, we do not see any effects on employment or hours. There is however a small decrease in labor income per hour, particularly for men, younger individuals, and those with higher education level. 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.

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-Callao versus other metropolitan areas. In particular, we compare the change in the number of Peruvians between 18 and 75 years old in both locations in 2016 (the year before the shock) and 2019 (the last year in our sample).

Table 7: Metropolitan areas' population

	by gender			
	Lima-Callao		Other MA	
Year	Men	Women	Men	Women
2016	3,296,277	3,603,489	1,230,106	1,397,207
2019	3,362,337	3,661,589	1,296,724	1,504,361
	by age			
	Lima-Callao		Other MA	
	18≤age≤40	41≤age≤75	18≤age≤40	41≤age≤75
2016	3,598,873	3,300,893	1,369,382	1,257,932
2019	3,430,936	3,592,989	1,375,789	1,425,296

As shown in table 7, there is a clear difference in the growth rate of Lima-Callao

[17] We show the results for the difference-in-difference between Lima-Callao and the aggregate of all the metropolitan areas in the donor pool in table A.9.

and other metropolitan areas. Population growth rate in Lima-Callao 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-Callao the Peruvian population between 18 and 40 decreased by 4.6% after the influx of Venezuelans, while in the other metropolitan areas it increased by 0.5%. Thus, there is some indirect evidence that the foreign migratory shock might have prevented individuals (particularly the young) to migrate to the capital city or produced domestic migration from Lima-Callao to other urban areas.

6 Final remarks

The recent mass migration from Venezuela to Peru is an unusual phenomenon for several reasons, chiefly among them the magnitude of it, its suddenness, and its surprising nature, at least form the viewpoint of the receiving country—in the course of a few months immigrant labor from Venezuela went from practically nil to ten percent of the labor force in Lima, the capital and most populated city in the country. Yet, instead of massive unemployment or other major disruptions in the labor market, what follows was a (relatively) smooth adjustment of the labor market to the newcomers.

Besides its magnitude, the Venezuelan migration episode had two other salient characteristics: the absence of big legal or cultural barriers for the newcomers in at least some segments of the labor market in Lima (the somewhat ill-defined "informal sector"), and the fact that the migrants were relatively more educated than the local labor force. Given these features, one can think of the Venezuelan migration as a shock to the labor force biased toward relatively high skills. We explore this idea on the context of a simple model of the job market.

Research on migration often focuses on the adjustment made by migrants to the conditions in the labor market, for instance the downgrading of the skills of migrants in the new environment, which can be likened to a trade barrier. Given the magnitude of the shock, we may expect it to have an effect also on the salaries and employment of the local labor force. In the model we propose, workers are heterogenous, and they can switch among different types of jobs depending on their productivity for different jobs and the relative rewards of different jobs. We show that mass migration must result in adjustments in relative salaries, a reallocation of the local labor force, or both.

To explore empirically the adjustment of the Lima labor market, we implement a synthetic control estimation, using as donor units the next metropolitan areas of the country, which received a significantly lower share of migrants. We find very small or nil effects on employment and hours worked. While we see a brief negative effect on labor income per hour, such effect quickly dissipates. As anticipated by the model, we see adjustments in the occupational structure of Lima and Callao: increases in unskilled jobs and decreases in white collar jobs, and, to a lower extent, in blue collar jobs, both for men and women. The growth in unskilled jobs is seen particularly for older workers, and for workers with high school or less, compared to those with some college or technical education.

We find some partial evidence of lower population growth in Lima than other cities during the period Venezuelan migrants arrive, potentially suggesting domestic out migration from Lima in response, especially for young workers, who are relatively more skilled in Peru. Just like adjustments in the employment structure, internal migration may have contributed to lessen the effect of foreign migration on relative salaries.

Mass migration is to some extent similar to trade opening. It creates opportunities for beneficial exchange that can be exploited in a relatively flexible market economy. Moreover, a relatively flexible job market, in which jobs are nor rigidly assigned 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 helped mitigate a humanitarian disaster and put back to work those who had being forced to leave their home.

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1.5

Appendix: Tables and figures

Table A.1: Metropolitan area's districts: Lima-Callao

MA	Department	Province	District	District Code
	15 Lima	01 Lima	01 Lima	150101
	15 Lima	01 Lima	02 Ancón	150102
	15 Lima	01 Lima	03 Ate	150103
	15 Lima	01 Lima	04 Barranco	150104
	15 Lima	01 Lima	05 Breña	150105
	15 Lima	01 Lima	06 Carabayllo	150106
	15 Lima	01 Lima	07 Chaclacayo	150107
	15 Lima	01 Lima	08 Chorrillos	150108
	15 Lima	01 Lima	09 Cieneguilla	150109
	15 Lima	01 Lima	10 Comas	150110
	15 Lima	01 Lima	11 El Agustino	150111
	15 Lima	01 Lima	12 Independencia	150112
	15 Lima	01 Lima	13 Jesús María	150113
	15 Lima	01 Lima	14 La Molina	150114
	15 Lima	01 Lima	15 La Victoria	150115
	15 Lima	01 Lima	16 Lince	150116
	15 Lima	01 Lima	17 Los Olivos	150117
	15 Lima	01 Lima	18 Lurigancho	150118
	15 Lima	01 Lima	19 Lurin	150119
	15 Lima	01 Lima	20 Magdalena del Mar	150120
	15 Lima	01 Lima	21 Pueblo Libre	150121
	15 Lima	01 Lima	22 Miraflores	150122
	15 Lima	01 Lima	23 Pachacamac	150123
	15 Lima	01 Lima	24 Pucusana	150124
Lima-Callao	15 Lima	01 Lima	25 Puente Piedra	150125
	15 Lima	01 Lima	26 Punta Hermosa	150126
	15 Lima	01 Lima	27 Punta Negra	150127
	15 Lima	01 Lima	28 Rímac	150128
	15 Lima	01 Lima	29 San Bartolo	150129
	15 Lima	01 Lima	30 San Borja	150130
	15 Lima	01 Lima	31 San Isidro	150131
	15 Lima	01 Lima	32 San Juan de Lurigancho	150132
	15 Lima	01 Lima	33 San Juan de Miraflores	150133
	15 Lima	01 Lima	34 San Luis	150134
	15 Lima	01 Lima	35 San Martín de Porres	150135
	15 Lima	01 Lima	36 San Miguel	150136
	15 Lima	01 Lima	37 Santa Anita	150137
	15 Lima	01 Lima	38 Santa María del Mar	150138
	15 Lima	01 Lima	39 Santa Rosa	150139
	15 Lima	01 Lima	40 Santiago de Surco	150140
	15 Lima	01 Lima	41 Surquillo	150141
	15 Lima	01 Lima	42 Villa El Salvador	150142
	15 Lima	01 Lima	43 Villa María del Triunfo	150143
	7 Callao	01 Prov. Const. del Callao	01 Callao	70101
	7 Callao	01 Prov. Const. del Callao	02 Bellavista	70102
	7 Callao	01 Prov. Const. del Callao	03 Carmen de la Legua Reynoso	70103
	7 Callao	01 Prov. Const. del Callao	04 La Perla	70104
	7 Callao	01 Prov. Const. del Callao	05 La Punta	70105
	7 Callao	01 Prov. Const. del Callao	06 Ventanilla	70106
	7 Callao	01 Prov. Const. del Callao	07 Mi Perú	70107

Table A.2: Metropolitan area's districts: donor pool

MA	Department	Province	District	District Code
Trujillo	13 La Libertad	01 Trujillo	01 Trujillo	130101
	13 La Libertad	01 Trujillo	02 El Porvenir	130102
	13 La Libertad	01 Trujillo	03 Florencia de Mora	130103
	13 La Libertad	01 Trujillo	04 Huanchaco	130104
	13 La Libertad	01 Trujillo	05 La Esperanza	130105
	13 La Libertad	01 Trujillo	06 Laredo	130106
	13 La Libertad	01 Trujillo	07 Moche	130107
	13 La Libertad	01 Trujillo	09 Salaverry	130109
	13 La Libertad	01 Trujillo	11 Víctor Larco Herrera	130111
Arequipa	4 Arequipa	01 Arequipa	01 Arequipa	40101
	4 Arequipa	01 Arequipa	02 Alto Selva Alegre	40102
	4 Arequipa	01 Arequipa	03 Cayma	40103
	4 Arequipa	01 Arequipa	04 Cerro Colorado	40104
	4 Arequipa	01 Arequipa	05 Characato	40105
	4 Arequipa	01 Arequipa	06 Chiguata	40106
	4 Arequipa	01 Arequipa	07 Jacobo Hunter	40107
	4 Arequipa	01 Arequipa	09 Mariano Melgar	40109
	4 Arequipa	01 Arequipa	10 Miraflores	40110
	4 Arequipa	01 Arequipa	11 Mollebaya	40111
	4 Arequipa	01 Arequipa	12 Paucarpata	40112
	4 Arequipa	01 Arequipa	15 Quequeña	40115
	4 Arequipa	01 Arequipa	16 Sabandía	40116
	4 Arequipa	01 Arequipa	17 Sachaca	40117
	4 Arequipa	01 Arequipa	22 Socabaya	40122
	4 Arequipa	01 Arequipa	23 Tiabaya	40123
	4 Arequipa	01 Arequipa	24 Uchumayo	40124
	4 Arequipa	01 Arequipa	26 Yanahuara	40126
	4 Arequipa	01 Arequipa	27 Yarabamba	40127
	4 Arequipa	01 Arequipa	28 Yura	40128
	4 Arequipa	01 Arequipa	29 José Luis Bustamante y Rivero	40129
Chiclayo	14 Lambayaque	01 Chiclayo	01 Chiclayo	140101
	14 Lambayaque	01 Chiclayo	03 Eten	140103
	14 Lambayaque	01 Chiclayo	04 Eten Puerto	140104
	14 Lambayaque	01 Chiclayo	05 José Leonardo Ortiz	140105
	14 Lambayaque	01 Chiclayo	06 La Victoria	140106
	14 Lambayaque	01 Chiclayo	08 Monsefú	140108
	14 Lambayaque	01 Chiclayo	12 Pimentel	140112
	14 Lambayaque	01 Chiclayo	13 Reque	140113
	14 Lambayaque	01 Chiclayo	14 Santa Rosa	140114
	14 Lambayaque	01 Chiclayo	18 Pomalca	140118
	14 Lambayaque	03 Lambayeque	01 Lambayeque	140301
	14 Lambayaque	03 Lambayeque	11 San José	140311
Piura	20 Piura	01 Piura	01 Piura	200101
	20 Piura	01 Piura	04 Castilla	200104
	20 Piura	01 Piura	05 Catacaos	200105
	20 Piura	01 Piura	15 Veintiséis de Octubre	200115
Iquitos	16 Loreto	01 Maynas	01 Iquitos	160101
	16 Loreto	01 Maynas	08 Punchana	160108
	16 Loreto	01 Maynas	12 Belén	160112
	16 Loreto	01 Maynas	13 San Juan Bautista	160113
Cusco	8 Cusco	01 Cusco	01 Cusco	80101
	8 Cusco	01 Cusco	04 San Jerónimo	80104
	8 Cusco	01 Cusco	05 San Sebastian	80105
	8 Cusco	01 Cusco	06 Santiago	80106
	8 Cusco	01 Cusco	08 Wanchaq	80108
Chimbote	2 Ancash	18 Santa	01 Chimbote	21801
	2 Ancash	18 Santa	03 Coishco	21803
	2 Ancash	18 Santa	09 Nuevo Chimbote	21809
Huancayo	12 Junin	01 Huancayo	01 Huancayo	120101
	12 Junín	01 Huancayo	07 Chilca	120107
	12 Junín	01 Huancayo	14 El Tambo	120114

Table A.3: Balance among predictors: outcomes prior to migration

		2013	2014	2015	2016
	Lima	0.6954	0.6844	0.6850	0.6944
Employment	Synthetic Lima	0.6965	0.6810	0.6915	0.6853
	Average donor pool	0.6948	0.6861	0.6906	0.6899
	Lima	31.7510	30.7268	31.3595	31.1141
Hours	Synthetic Lima	31.3403	30.9785	30.6799	30.2357
	Average donor pool	30.7974	30.5785	30.5246	29.9080
	Lima	8.1458	9.6610	9.6548	11.1462
Labor income per hour	Synthetic Lima	7.2926	8.0342	8.1755	9.9059
	Average donor pool	6.9216	7.6846	8.3938	9.0279
	Lima	0.3974	0.3695	0.3718	0.3668
Informality	Synthetic Lima	0.3970	0.4001	0.4174	0.4024
	Average donor pool	0.4487	0.4443	0.4576	0.4415
	Lima	0.0834	0.0850	0.0798	0.0843
Professional jobs	Synthetic Lima	0.0892	0.0785	0.0740	0.0891
	Average donor pool	0.0868	0.0820	0.0786	0.0834
	Lima	0.2821	0.2851	0.2701	0.2828
White collar jobs	Synthetic Lima	0.2849	0.2622	0.2741	0.2735
	Average donor pool	0.2770	0.2584	0.2548	0.2633
	Lima	0.1652	0.1576	0.1666	0.1622
Blue collar jobs	Synthetic Lima	0.1590	0.1703	0.1734	0.1689
	Average donor pool	0.1702	0.1725	0.1797	0.1754
	Lima	0.1646	0.1566	0.1685	0.1651
Unskilled jobs	Synthetic Lima	0.1531	0.1614	0.1765	0.1632
	Average donor pool	0.1608	0.1732	0.1775	0.1678

Table A.4: Balance among predictors for men's sample

		2013	2014	2015	2016
Employment	Lima-Callao	0.8053	0.7847	0.7992	0.8106
	Synthetic Lima-Callao	0.8099	0.7972	0.7982	0.7798
	Average donor pool	0.7929	0.7915	0.7917	0.7833
Hours	Lima-Callao	38.6610	37.4955	38.5151	38.5764
	Synthetic Lima-Callao	38.7620	37.7040	37.9276	36.7108
	Average donor pool	37.5447	36.9608	37.2321	36.3695
Labor income per hour	Lima-Callao	8.8794	10.7316	10.3973	11.9218
	Synthetic Lima-Callao	8.5196	9.1725	9.3164	11.5885
	Average donor pool	7.7936	8.5519	9.4620	10.2490
Informality	Lima-Callao	0.4351	0.3970	0.4177	0.4029
	Synthetic Lima-Callao	0.4016	0.4250	0.4463	0.4303
	Average donor pool	0.4785	0.4784	0.4817	0.4666
Professional jobs	Lima-Callao	0.0867	0.0820	0.0795	0.0789
	Synthetic Lima-Callao	0.0823	0.0779	0.0677	0.0976
	Average donor pool	0.0926	0.1023	0.0833	0.0941
White collar jobs	Lima-Callao	0.2746	0.2720	0.2570	0.2791
	Synthetic Lima-Callao	0.2815	0.2440	0.2554	0.2656
	Average donor pool	0.2583	0.2382	0.2423	0.2390
Blue Collar jobs	Lima-Callao	0.2908	0.2823	0.3008	0.2929
	Synthetic Lima-Callao	0.2901	0.3012	0.3089	0.2969
	Average donor pool	0.2844	0.2767	0.2933	0.2858
Unskilled jobs	Lima-Callao	0.1532	0.1484	0.1619	0.1596
	Synthetic Lima-Callao	0.1371	0.1502	0.1819	0.1538
	Average donor pool	0.1575	0.1743	0.1729	0.1644

Table A.5: Balance among predictors for women's sample

		2013	2014	2015	2016
	Lima-Callao	0.5932	0.5940	0.5818	0.5882
Employment	Synthetic Lima-Callao	0.6033	0.5782	0.5925	0.5983
	Average donor pool	0.5987	0.5813	0.5878	0.5971
	Lima-Callao	25.3291	24.6293	24.8956	24.2941
Hours	Synthetic Lima-Callao	25.2079	24.6449	24.5816	24.3345
	Average donor pool	24.3773	23.6637	23.7121	23.6399
	Lima-Callao	7.2200	8.3857	8.7325	10.1709
Labor income per hour	Synthetic Lima-Callao	5.8817	6.2636	7.8586	7.4695
	Average donor pool	5.9069	6.6336	7.1404	7.6491
	Lima-Callao	0.3624	0.3448	0.3303	0.3337
Informality	Synthetic Lima-Callao	0.3933	0.3764	0.3912	0.3797
	Average donor pool	0.4071	0.3774	0.3904	0.3859
	Lima-Callao	0.0803	0.0877	0.0801	0.0892
Professional jobs	Synthetic Lima-Callao	0.0954	0.0791	0.0800	0.0810
	Average donor pool	0.0958	0.0987	0.0909	0.0947
	Lima-Callao	0.2891	0.2970	0.2819	0.2864
White collar jobs	Synthetic Lima-Callao	0.2869	0.2815	0.2899	0.2932
	Average donor pool	0.2995	0.2883	0.2921	0.2973
	Lima-Callao	0.0485	0.0453	0.0454	0.0425
Blue collar jobs	Synthetic Lima-Callao	0.0557	0.0493	0.0548	0.0568
	Average donor pool	0.0522	0.0455	0.0499	0.0556
	Lima-Callao	0.1753	0.1640	0.1744	0.1701
Unskilled jobs	Synthetic Lima-Callao	0.1701	0.1738	0.1776	0.1623
	Average donor pool	0.1512	0.1487	0.1548	0.1495

Table A.6: Balance among predictors, by age

		2013	2014	2015	2016
Between 18 and 40 years old					
Employment	Lima-Callao	0.7171	0.6982	0.6919	0.6924
	Synthetic Lima-Callao	0.7008	0.6891	0.6774	0.6771
	Average donor pool	0.6849	0.6655	0.6691	0.6620
White collar jobs	Lima-Callao	0.3260	0.3306	0.3129	0.3126
	Synthetic Lima-Callao	0.3061	0.2903	0.2940	0.3092
	Average donor pool	0.2981	0.2763	0.2816	0.2879
Blue collar jobs	Lima-Callao	0.1601	0.1545	0.1593	0.1546
	Synthetic Lima-Callao	0.1699	0.1588	0.1696	0.1496
	Average donor pool	0.1474	0.1351	0.1528	0.1403
Unskilled jobs	Lima-Callao	0.1543	0.1381	0.1505	0.1484
	Synthetic Lima-Callao	0.1407	0.1552	0.1579	0.1385
	Average donor pool	0.1526	0.1608	0.1557	0.1482
Between 41 and 75 years old					
Employment	Lima-Callao	0.6721	0.6699	0.6774	0.6965
	Synthetic Lima-Callao	0.6838	0.6835	0.6949	0.6937
	Average donor pool	0.6957	0.6959	0.6972	0.7051
White collar jobs	Lima-Callao	0.2354	0.2372	0.2224	0.2505
	Synthetic Lima-Callao	0.2382	0.2277	0.2322	0.2290
	Average donor pool	0.2600	0.2525	0.2554	0.2522
Blue collar jobs	Lima-Callao	0.1707	0.1610	0.1748	0.1703
	Synthetic Lima-Callao	0.1595	0.1733	0.1780	0.1973
	Average donor pool	0.1770	0.1747	0.1743	0.1845
Unskilled jobs	Lima-Callao	0.1756	0.1762	0.1887	0.1832
	Synthetic Lima-Callao	0.1772	0.1643	0.1945	0.1841
	Average donor pool	0.1559	0.1607	0.1713	0.1649

Table A.7: Balance among predictors, by education level

		2013	2014	2015	2016
Complete high school or less					
Employment	Lima-Callao	0.66521	0.65215	0.66038	0.67154
	Synthetic Lima-Callao	0.67454	0.65376	0.67273	0.66033
	Average donor pool	0.6734	0.6596	0.6671	0.6637
White collar jobs	Lima-Callao	0.2144	0.2163	0.2044	0.2127
	Synthetic Lima-Callao	0.2118	0.1935	0.2062	0.2223
	Average donor pool	0.2981	0.2763	0.2816	0.2879
Blue collar jobs	Lima-Callao	0.2193	0.2152	0.2239	0.2226
	Synthetic Lima-Callao	0.2362	0.2332	0.2223	0.2203
	Average donor pool	0.2184	0.2104	0.2141	0.2156
Unskilled jobs	Lima-Callao	0.2268	0.2139	0.2294	0.2325
	Synthetic Lima-Callao	0.2214	0.2259	0.2462	0.2128
	Average donor pool	0.2212	0.2262	0.2307	0.2189
At least some college or technical education, beyond high school					
Employment	Lima-Callao	0.7388	0.7327	0.7226	0.7247
	Synthetic Lima-Callao	0.7250	0.7205	0.7235	0.7120
	Average donor pool	0.7118	0.7064	0.7030	0.7061
White collar jobs	Lima-Callao	0.3804	0.3890	0.3703	0.3769
	Synthetic Lima-Callao	0.3719	0.3338	0.3536	0.3468
	Average donor pool	0.3463	0.3235	0.3336	0.3227
Blue collar jobs	Lima-Callao	0.0865	0.0711	0.0792	0.0810
	Synthetic Lima-Callao	0.0725	0.0836	0.0977	0.0952
	Average donor pool	0.0863	0.0835	0.0975	0.0991
Unskilled jobs	Lima-Callao	0.0738	0.0701	0.0754	0.0744
	Synthetic Lima-Callao	0.0691	0.0759	0.0804	0.0826
	Average donor pool	0.0660	0.0780	0.0759	0.0829

Table A.8: Difference in difference estimations: Lima vs Arequipa

	All	Women	Men	18≤age≤40	41≤age≤75	Low education	High education
Employment							
2017S1 - 2018S1	0.00237	0.0197	-0.0164	0.00495	-0.00313	0.0212	-0.0219
	(0.0117)	(0.0177)	(0.0150)	(0.0160)	(0.0155)	(0.0170)	(0.0160)
2018S2 - 2019S2	-0.00609	-0.0163	0.00672	0.00100	-0.00407	0.0128	-0.0297*
	(0.0121)	(0.0180)	(0.0158)	(0.0168)	(0.0156)	(0.0175)	(0.0166)
Hours							
2017S1 - 2018S1	-0.250	0.823	-1.410	-0.0640	-0.601	0.305	-1.041
	(0.669)	(0.923)	(0.962)	(0.888)	(0.921)	(0.995)	(0.881)
2018S2 - 2019S2	-0.397	-0.434	-0.263	-0.249	-0.116	-0.732	-0.220
	(0.690)	(0.960)	(0.989)	(0.913)	(0.959)	(1.042)	(0.896)
Labor income per hour							
2017S1 - 2018S1	-0.110	0.0444	-0.226	0.104	-0.350*	-0.0364	-0.232
	(0.135)	(0.191)	(0.187)	(0.180)	(0.200)	(0.180)	(0.202)
2018S2 - 2019S2	-0.350**	-0.336	-0.393**	-0.247	-0.422**	-0.305	-0.434**
	(0.144)	(0.205)	(0.198)	(0.191)	(0.211)	(0.191)	(0.214)
Informality							
2017S1 - 2018S1	0.0164	0.0409**	-0.0102	0.0152	0.0169	0.0189	0.0155
	(0.0126)	(0.0173)	(0.0184)	(0.0177)	(0.0178)	(0.0187)	(0.0169)
2018S2 - 2019S2	0.00282	0.00840	-0.00237	0.00961	-0.00263	0.0370*	-0.0322*
	(0.0131)	(0.0180)	(0.0191)	(0.0185)	(0.0185)	(0.0191)	(0.0179)
Professional jobs							
2017S1 - 2018S1	-0.0125*	0.00582	-0.0328***	-0.0201**	-0.00673	-0.00346	-0.0247*
	(0.00691)	(0.00898)	(0.0106)	(0.00993)	(0.00939)	(0.00234)	(0.0139)
2018S2 - 2019S2	-0.00204	-0.00905	0.00579	0.00245	-0.00454	0.000548	-0.00756
	(0.00689)	(0.00977)	(0.00967)	(0.00949)	(0.00977)	(0.00204)	(0.0139)
White collar jobs							
2017S1 - 2018S1	-0.00294	-0.00119	-0.00573	0.00510	-0.0101	0.00288	-0.0131
	(0.0115)	(0.0166)	(0.0156)	(0.0163)	(0.0160)	(0.0150)	(0.0175)
2018S2 - 2019S2	-0.0178	-0.0234	-0.0120	-0.00385	-0.0282*	-0.0217	-0.0191
	(0.0119)	(0.0173)	(0.0159)	(0.0169)	(0.0165)	(0.0157)	(0.0179)
Blue collar jobs							
2017S1 - 2018S1	0.0150	-0.00119	0.0271	0.0144	0.0144	0.0192	0.0144
	(0.00937)	(0.0166)	(0.0173)	(0.0126)	(0.0136)	(0.0144)	(0.0116)
2018S2 - 2019S2	-0.0175*	-0.0234	-0.0383**	-0.0177	-0.0147	-0.0147	-0.0159
	(0.00992)	(0.0173)	(0.0183)	(0.0134)	(0.0142)	(0.0150)	(0.0127)
Unskilled jobs							
2017S1 - 2018S1	0.00279	0.00981	-0.00490	0.00550	-0.000634	0.00261	0.00156
	(0.00966)	(0.0136)	(0.0137)	(0.0126)	(0.0147)	(0.0161)	(0.0103)
2018S2 - 2019S2	0.0313***	0.0131	0.0512***	0.0201	0.0434***	0.0486***	0.0129
	(0.00952)	(0.0139)	(0.0128)	(0.0126)	(0.0142)	(0.0156)	(0.0104)
N	83,916	43,939	39,977	42,097	41,819	45,614	38,302

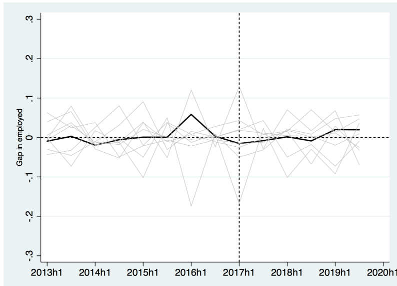
Notes: Include controls and time and city effects. Labor income per hour calculated only over those employed.

Table A.9: Difference in difference estimations: all metropolitan areas

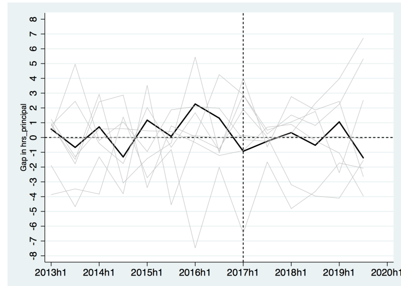
	All	Women	Men	18≤age≤40	41≤age≤75	Low education	High education
Employment							
2017S1 - 2018S1	0.00158	0.00828	-0.00668	0.000915	-0.00202	0.00378	-0.0054
	(0.00684)	-0.0103	(0.00880)	(0.00941)	(0.00899)	(0.00915)	(0.0102)
2018S2 - 2019S2	-0.00715	-0.0178*	0.00468	-0.0190**	0.00487	0.00303	-0.0249**
	(0.00694)	-0.0104	(0.00902)	(0.00962)	(0.00908)	(0.00938)	(0.0102)
Hours							
2017S1 - 2018S1	-0.169	0.125	-0.536	-0.409	-0.180	0.315	-0.993*
	(0.377)	-0.521	(0.544)	(0.510)	(0.515)	(0.522)	(0.533)
2018S2 - 2019S2	-0.386	-0.787	0.0638	-0.631	-0.183	-0.00627	-1.101**
	(0.384)	-0.535	(0.548)	(0.519)	(0.521)	(0.535)	(0.537)
Labor income per hour							
2017S1 - 2018S1	0.0716	0.132	0.0208	0.127	-0.0105	0.101	0.00438
	-0.0774	(0.115)	(0.105)	(0.101)	(0.118)	(0.0963)	(0.127)
2018S2 - 2019S2	-0.198**	-0.195*	-0.211*	-0.164	-0.225*	-0.112	-0.335**
	-0.0801	(0.117)	(0.109)	(0.105)	(0.121)	(0.0998)	(0.130)
Informality							
2017S1 - 2018S1	0.0200***	0.0288***	0.00988	0.0268***	0.0108	0.0175*	0.0227**
	(0.00734)	-0.0101	(0.0107)	(0.0104)	(0.0103)	(0.0102)	(0.0105)
2018S2 - 2019S2	0.0193***	0.0111	0.0280**	0.0209**	0.0159	0.0282***	0.00642
	(0.00746)	-0.0102	(0.0109)	(0.0106)	(0.0104)	(0.0103)	(0.0106)
Professional jobs							
2017S1 - 2018S1	0.00326	-0.00255	-0.0328***	0.00254	0.00209	-0.00131	0.00703
	(0.00376)	(0.00546)	(0.0106)	(0.00519)	(0.00531)	(0.00113)	(0.00859)
2018S2 - 2019S2	-0.00209	0.00479	0.00579	0.00349	-0.00847	0.00116	-0.00806
	(0.00389)	(0.00555)	(0.00967)	(0.00545)	(0.00543)	(0.00128)	(0.00876)
White collar jobs							
2017S1 - 2018S1	-0.0105	-0.00749	-0.00573	-0.0189**	-0.000537	-0.00951	-0.00414
	(0.00673)	(0.00931)	(0.0156)	(0.00966)	(0.00930)	(0.00842)	-0.00677
2018S2 - 2019S2	-0.0236***	-0.0191**	-0.0120	-0.0334***	-0.0102	-0.0211**	-0.014
	(0.00683)	(0.00942)	(0.0159)	(0.00988)	(0.00934)	(0.00854)	(0.0109)
Blue collar jobs							
2017S1 - 2018S1	-0.00207	-0.00703	0.0271	-0.00133	-0.00461	-0.00598	-0.0298***
	(0.00537)	(0.00994)	(0.0173)	(0.00726)	(0.00779)	(0.00785)	(0.011)
2018S2 - 2019S2	-0.00410	-0.0121	-0.0383**	-0.00764	-0.000872	-0.00375	0.00358
	(0.00544)	(0.0101)	(0.0183)	(0.00738)	(0.00787)	(0.00795)	(0.00661)
Unskilled jobs							
2017S1 - 2018S1	0.0109*	0.0104	-0.00490	0.0186**	0.00104	0.0206**	-0.00201
	(0.00565)	(0.00818)	(0.0137)	(0.00762)	(0.00831)	(0.00868)	(0.0063)
2018S2 - 2019S2	0.0226***	0.0311***	0.0512***	0.0186**	0.0245***	0.0267***	0.0170***
	(0.00573)	(0.00825)	(0.0128)	(0.00769)	(0.00842)	(0.00888)	(0.00629)
N	138,013	72,907	65,106	69,266	68,747	75,694	62,319

Notes: Include controls and time and city effects. Labor income per hour calculated only over those employed.

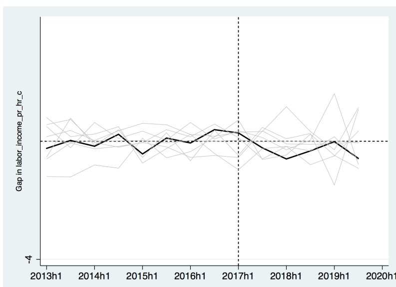
Figure A.1: Simulated permutations: men sample



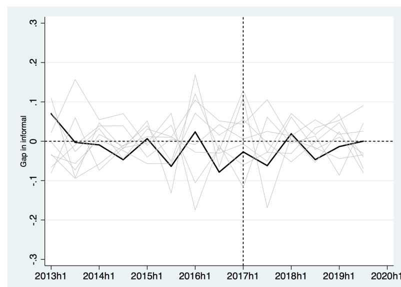
(a) Employment



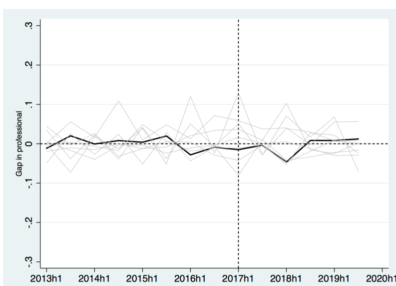
(b) Hours



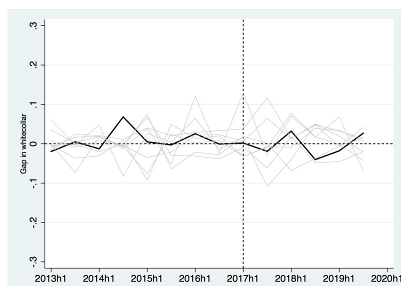
(c) Labor income per hour



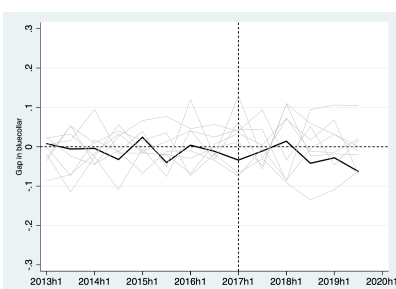
(d) Informality



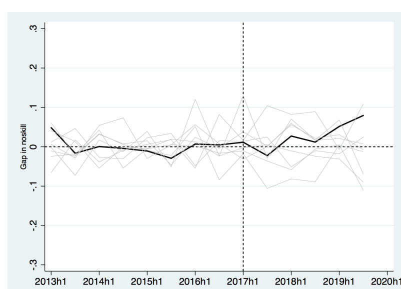
(e) Professional jobs



(f) White collar jobs

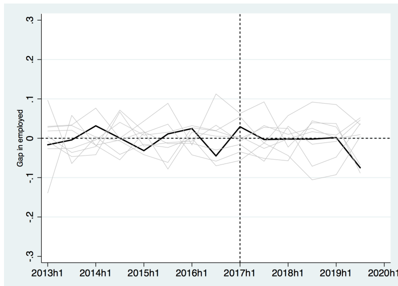


(g) Blue collar jobs

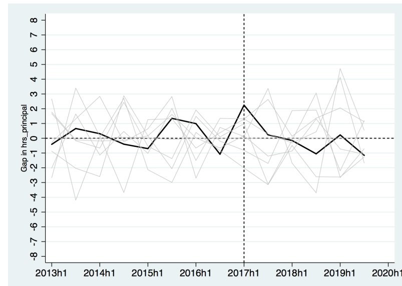


(h) Unskilled jobs

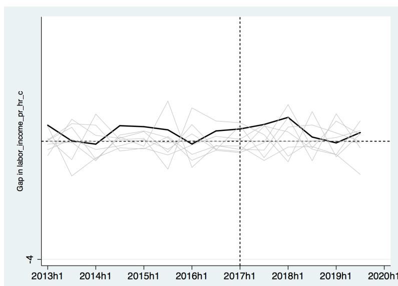
Figure A.2: Simulated permutations: women sample



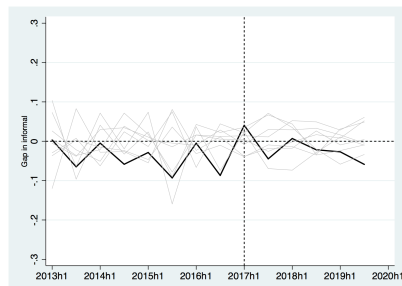
(a) Employment



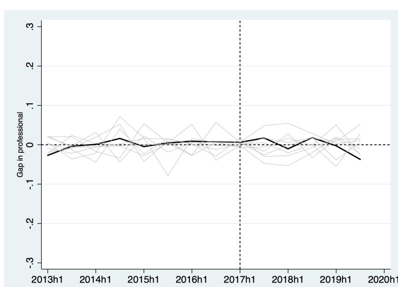
(b) Hours



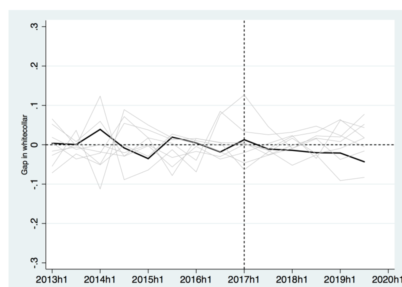
(c) Labor income per hour



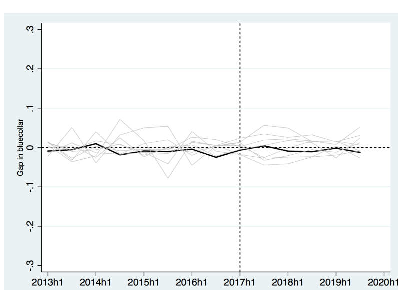
(d) Informality



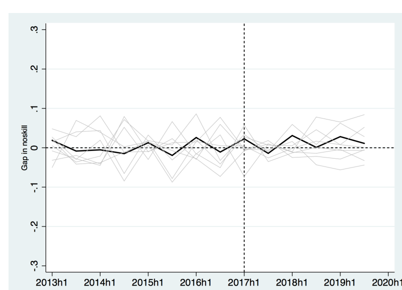
(e) Professional jobs



(f) White collar jobs

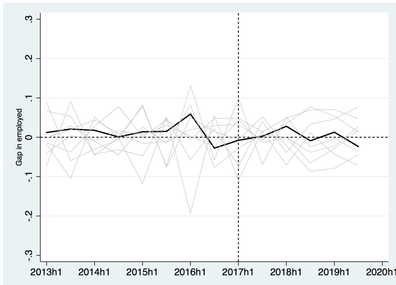


(g) Blue collar jobs

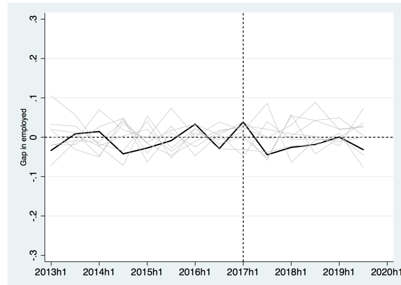


(h) Unskilled jobs

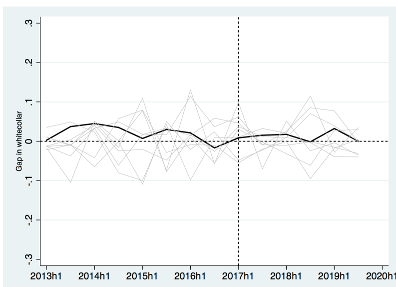
Figure A.3: Simulated permutations: sample by age



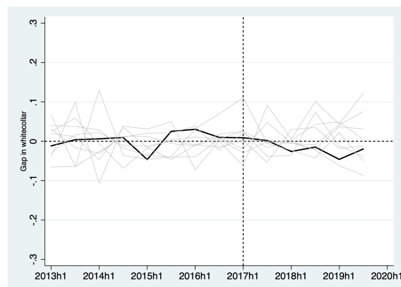
(a) Employment: 18≤age≤40



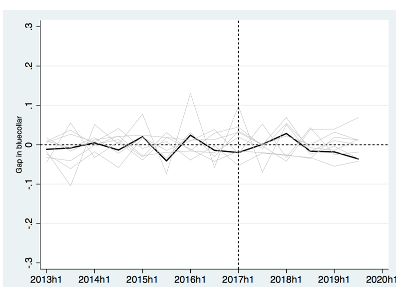
(b) Employment: 41≤age≤75



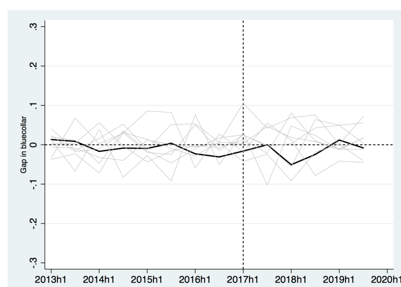
(c) White collar: 18≤age≤40



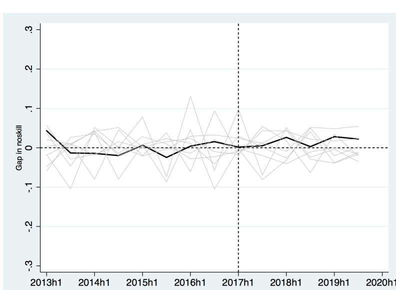
(d) White collar: 41≤age≤75



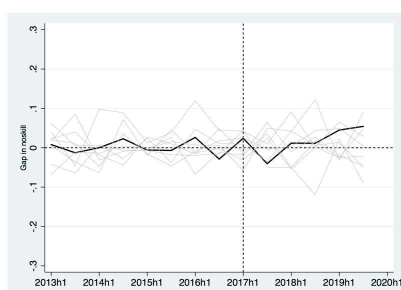
(e) Blue collar: 18≤age≤40



(f) Blue collar: 41≤age≤75

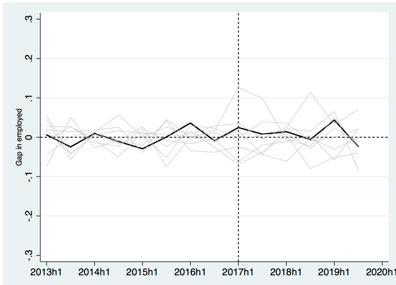


(g) Unskilled: 18≤age≤40

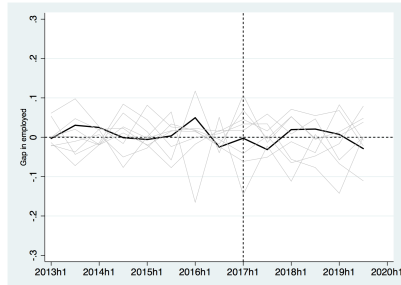


(h) Unskilled: 41≤age≤75

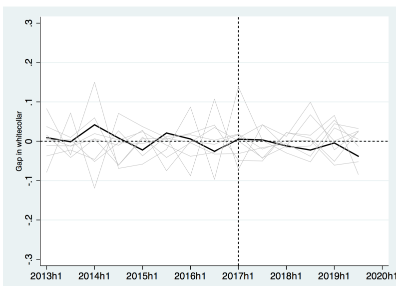
Figure A.4: Simulated permutations: sample by educational level



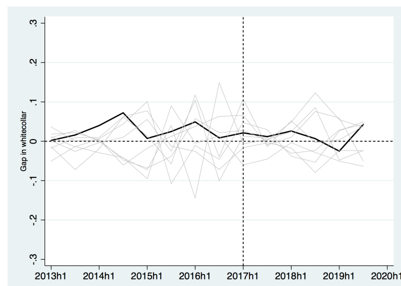
(a) Employment: low education



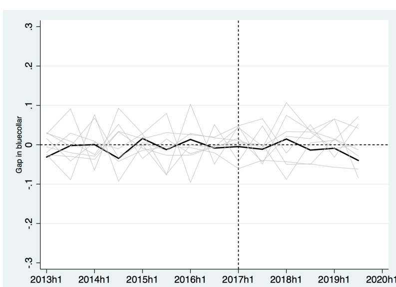
(b) Employment: high education



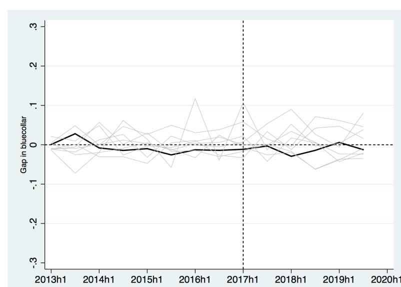
(c) White collar: low education



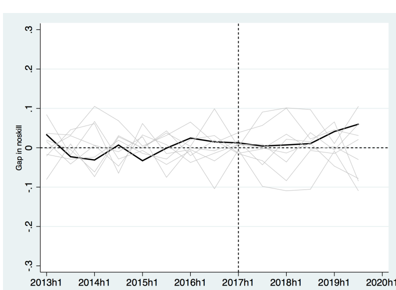
(d) White collar: high education



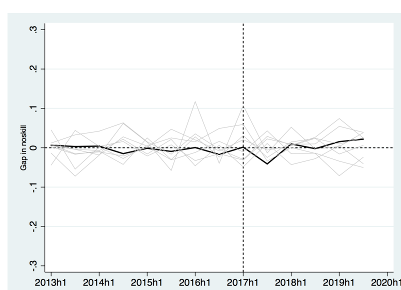
(e) Blue collar: low education



(f) Blue collar: high education



(g) Unskilled: low education



(h) Unskilled: high education