# The Venezuelan Diaspora: Evidence from the Peruvian Labor Market

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**Abstract**

This paper studies the unprecedented inflow of Venezuelan immigrants to Peru with a particular focus on Peruvian-born employment and wages. The Peruvian labor market's main features are (1) a large informal sector with only 28% of workers covered by employer health insurance, and (2) a relatively low-skilled workforce, two-thirds of whom have obtained a high school degree or less. By December 2018, Peru received more than 630,000 Venezuelan immigrants, most of whom arrived between 2017 and 2018, and approximately 85% of the immigrants settled in Lima and Callao provinces, the largest metropolitan area in Peru. This immigrant influx represents an 5.9% increase in the 2017 population in Lima and Callao and a 7.5% increase of the working-age population. I study the impact of the net inflow of immigrants in Lima and Callao between 2014 and 2018 using a difference-in-difference approach at the neighborhood level. Findings show that high-immigration neighborhoods have, on average, 2 percentage points higher employment and 2% less weekly wages than low-immigration areas after 2017. These effects on Peruvian labor market outcomes are driven by the formal sector, and primarily affect low-skilled Peruvians. The results imply that the immigration shock did not crowd-out Peruvian-born employment, nor the less skilled workers who usually are also constrained by the minimum wage policy. I suggest that the Lima-Callao metropolitan area absorbed the 7.5% labor supply increase between 2017 and 2018 due the flexibility of the informal labor market.

Keywords: immigration, employment, wages, informal sector, skills, local labor market, neighborhoods.

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## 1. Introduction

Venezuela's economic and political crisis in the 2010s have caused an unprecedented inflow of migrants to Peru (Restuccia, 2018; UNHCR & IOM, 2022). Peru has received more than 630,000 Venezuelan-born immigrants from 2016 to 2018, representing a 2.4% increase in the 2017 country's population.[2] More than 85% of this immigration influx settled in the main metropolitan area of Lima and Callao provinces,[3] representing a 7.5% increase in their 2017 working-age population. Like many places that have received mass immigration, Peruvians have raised public concerns about local employment (Rosales, 2018). Workers are presumably highly substitutable because most of the labor force in Peru belongs to the informal sector (INEI, 2018b). In the informal sector, workers do not have regular and mandatory employee benefits in Peru such as health coverage, retirement contributions, and parental leave, amongst other types of benefits (INEI, 2018b).[4] Previous studies have shown that most immigrant workers compete with local employment for these low-benefitting jobs (Bahar et al., 2021; Caruso et al., 2019; Santamaria, 2020a). Therefore, one might ask how the Peruvian labor market would respond to this sharp and fast Venezuelan immigration to Lima and Callao.

This empirical study looks at the effect of Venezuelan-born migration on the labor market outcomes in the neighborhoods of Lima and Callao provinces between 2014 to 2018. Peru is a country without a historic influx of immigrants, unlike the massive migration to the U.S. in the 19th century or the subsequent migration of Mexican immigrants to the US (Abramitzky et al.,

[2] By June 2022, more than 1.2 millions Venezuelan https://www.r4v.info (UNHCR & IOM, 2022), which represents 4.1% increase of the 2017 population, 10.8% increase of the 2017 Lima and Callao population, and a 13.6% increase of the 2017 working-age population in Lima and Callao.
[3] The total population in Peru in 2017 was 29,381,884; 33% of that total population lives in Lima and Callao, 9.5 million in 2017 (INEI, 2017).
[4] The workers characteristics in the informal labor market in a developing country are parallel to the recent rise in alternative work or outsourcing in the US labor market (Katz & Krueger, 2017).

2014; Monras, 2020; Sequeira et al., 2020). Further, Peru's sizeable informal labor sector offers immigrant workers low paid jobs that are better options than the options remaining in their home country (Borjas, 1987, 1991; Buxton, 2005; INEI, 2018b). In the case of Venezuela, the main push factor for this migration is the 2017 Venezuelan economic and political crises that drove many immigrants to Latin America and the rest of the world (Bull, 2020; Restuccia, 2018). Finally, Peru also appeals to Venezuelan immigrants, despite its geographic distance, because it is the first Latin American country with an immigration policy that offers Venezuelan immigrants easy access to legal status (Acosta et al., 2019; Decreto Supremo N° 002-2017-IN, 2017). Thus, Venezuelan immigration to Peru highlights a unique, modern, large-scale immigration where a middle-income country with no previous experience receiving a foreign labor force is the destination.

I exploit the spatial variation of the immigration net inflow by neighborhood in a difference-in-difference research design. More specifically, I compare Peruvian labor outcomes in high-immigration neighborhoods with low-immigration inflow areas between 2016 and 2018. The underlying identification assumption is the parallel trends of the Peruvian labor outcomes between high and low immigrant neighborhoods. The main econometric challenge for identifying the causal effect of immigration on native labor market outcomes is that a labor demand shock might violate the trends assumption affecting the Peruvian labor market outcomes and the Venezuelan location decisions (Kennan & Walker, 2011). Typically, the immigration literature solves this estimation issue using an IV approach (Becker & Ferrara, 2019). I argue that immigration in this setting is driven mainly by the Venezuelan crisis, akin to Monras' push factor argument surrounding sharp and fast inflows of immigrants (2020). Further, it is less likely there will be differential labor demand shocks by neighborhood due to the decreased economic growth rate before 2017 (IPE, 2019). Based on suggestive evidence, the parallel trends null hypothesis cannot be rejected with an event-study plot of the difference in Peruvian employment and wages for low and high-immigrant neighborhoods.

I find a positive effect of Venezuelan-born immigration on Peruvian employment and a negative impact on their weekly wages. My results suggest that there is 2 percentage points more employment and 2% less in domestic workers' salaries in high immigrant areas relative to neighborhoods with a low inflow of Venezuelan immigrants. In absolute numbers, this represents an increase of 144,000 Peruvian working-age employees but a reduction of $4.6 USD weekly wages. While previous studies that looked into Peru found a negligible effect of immigration on employment and wages for the whole country, this study found a positive impact on employment rate that was three times higher in Lima-Callao than the estimate for Peru, and detected negative effects on Peruvian wages (Boruchowicz et al., 2021; Denisse & Morales, 2020; Gröger, 2021; Vera & Jimenez, 2022). The main results on the Peruvian labor market outcomes are driven by the formal sector, where the low-skilled Peruvian working-age population experiences a negative effect on wages rather than employment. These results imply that I do not find a substantial decrease in low-skilled Peruvian-born employment in both the formal and informal sectors in the neighborhoods of Lima and Callao.

The economic interpretation of these results has the following considerations using a competitive labor market model (Ottaviano & Peri, 2012; Peri, 2016). First, given that most of the Peruvian labor force is in the informal sector and 88% of Venezuelan workers do not have formal contracts, one can reasonably assume most of the labor supply shock due to this immigration inflow affects the informal sector (INEI, 2018b, 2018a). Depending on the degrees of substitution between formal and informal labor, the immigration shock might displace formal native jobs when firms hire both types of workers (Delgado-Prieto, 2022a; Kleemans & Magruder, 2018). Further, most of the labor force is relatively low-skilled in Lima and Callao; thus, depending on the degree of imperfect substitutability between low- and high-skilled labor units within sectors, the theory suggests a crowd-out of low-skilled local employment in the informal sector (Kleemans & Magruder, 2018). Yet, in this case, an increase in Peruvian employment in the formal sector suggests a high degree of imperfect substitution between Peruvians and Venezuelans. More importantly, I can rule out the crowd-out of low-skilled employees in the informal and formal sectors, which are usually the skill groups that compete for low-paid jobs among immigrant workers.

Based on the findings of this study, my contribution to immigration and urban literature are twofold. First, this paper adds evidence to the recent articles studying the effect of Venezuelans in Peru. Following the work at the national (Vera & Jimenez, 2022) and the provincial level (Boruchowicz et al., 2021; Denisse & Morales, 2020; Groeger et al., 2022), I extend the analysis by using the spatial variation of the net inflow at the district level, which is consistent with the neighborhoods in Lima and Callao.[5] In collaboration with the Peruvian National Institute of Statistics (INEI), I matched their neighborhood block units to their respective districts, and matched the Labor Force Survey in Lima and Callao with their novel Venezuelan Survey (ENPOVE). The combination of this data allowed me to closely track the shock of Venezuelans at this disaggregated geographic level to understand the labor market response across neighborhoods in Lima and Callao.

Second, I contribute to the urban literature on neighborhood dynamics. I document the Peruvian labor market characteristics and the salient features of immigration shock across districts. These

[5] Peru has three geographical administrative units. From the largest to the smallest division, Peru is divided in departments (similar to state levels), provinces, and districts (municipality level). For further information see https://www.distrito.pe

details are important since previous work showed *sorting of workers* across metropolitan areas (Chetty et al., 2013, 2016; Graham, 2018; Kling et al., 2007). One can interpret the main findings as similar to a local average treatment effect (LATE) (Angrist & Pischke, 2009; Cunningham, 2021). Under the condition of higher employment, lower-paid jobs, lower-skilled labor force, and higher informality in high-immigration neighborhoods, LATE means that Peruvian employment increased in this area when compared to low-immigration neighborhoods after the 2016-2018 Venezuelan influx.

The remainder of the paper is organized as follows. In Section 2, I provide an overview of the institutional background about the Venezuelan crisis, its significance in Latin America, and the Peruvian labor market's general characteristics. Then, I describe the empirical approach in an ideal experiment, the difference-in-difference specification, and its identification assumption in Section 3. Section 4 explains the variable of interest measurement based on empirical data and documents influx characteristics to validate the identification strategy. The results of this study, in Section 5, are then explained by the heterogeneous effect analysis of the Venezuelan influx on Peruvian wages and employment. In Section 6, I briefly discuss the standard IV approach from the immigration literature in similar settings and, finally, I provide several concluding remarks on the Peruvian labor market response to the recent Venezuelan immigration in Section 7.

## 2. Institutional Background of the Venezuelan Influx in Peru

This section briefly describes the Venezuelan crisis and the major differences between Peru from the rest of the region. Along with this, I provide details on the institutional background of the Peruvian labor market characteristics and economic condition.

## 2.1. The Inflow of Immigrants due to the Crisis in Venezuela and the Peruvian Immigration Policy for Venezuelan-born Immigrants

The Venezuelan influx is the second largest refugee crisis in the world, with 6.8 million citizens seeking better opportunities and 83% of whom are going to Latin America and the Caribbean (UNHCR & IOM, 2022)[6]. A combination of historical, political, and economic factors has contributed to the Venezuelan diaspora since 2010 (Restuccia, 2018). Venezuela was one of the wealthiest countries in Latin America in the 1970s. However, the nationalization of the oil industry in 1976, the debt crisis in the 1980s, and the political instability with electoral irregularities since the 2000s contributed to the Venezuelan crisis (Buxton, 2005; Corrales, 2020; Restuccia, 2018). Acosta et al. (2019) argue that Nicolas Maduro worsened the economic and political conditions after the death of President Hugo Chavez in 2013. Regardless of the origin of the political crisis, Venezuela's economy started 2016 with the hyperinflation phenomenon, shortages, and a poorer public services provision which includes education, health care attention, and a lack of essential provision of water and electricity (Restuccia, 2018). These challenging conditions has lead citizens from different economic backgrounds to migrate to other countries for better life conditions (Borjas, 1987; Kennan & Walker, 2011; UNHCR & IOM, 2022).

Despite being a non-neighboring country, Peru is the second largest destination for Venezuelan-born immigrants. Colombia is the first destination country, having received around 2.48 million migrants since 2015, or two times that of Peru (see Figure A.1).[7] Yet, the distance between Venezuela's capital and Peru's capital (1710 miles) is three times larger than the distance between

[6] The estimate of 6.8 million Venezuelan refugees is measured in October, 2022 from the website https://www.r4v.info (UNHCR & IOM, 2022).
[7] Similarly, the 2.48 million Venezuelan refugees in Colombia is measured in September, 2022 from the website https://www.r4v.info (UNHCR & IOM, 2022).

Venezuela's capital and Colombia's (638 miles) (Georg, 2022).[8] Thus, one might expect that fewer immigrants would travel by car or on foot from Caracas to Lima, as in Colombia's case.

One potential explanation for Peru as the second most popular destination country for Venezuelan immigrants despite this distance is the Peruvian immigration policy. Peru is the first country to introduce a working permit policy in Latin America which is a pathway to a legal status (Acosta et al., 2019). This immigration policy intends to integrate the Venezuelan working-age population into the formal labor force and provide public good services. This permit was introduced in January 2017, with only a 1% rejection rate of Venezuelan applicants in the first year (Decreto Supremo N° 002-2017-IN, 2017; OGPP, 2018). In contrast, Colombia established the Special Permanence Permit for Venezuelans by the end of July 2017 (Ibanez et al., 2021; Migracion Colombia, 2017; Ministerio de Relaciones Exteriores, 2017).[9] More importantly, Peru received Venezuelan regularizations for a longer time than Colombia. The Peruvian administration opened the registration between February 2017 and December 2018, while the application window was only five months in Colombia, from August to December 2018 (Acosta et al., 2019; Ibanez et al., 2021). Thus, in line with the welfare magnet hypothesis, it is possible that immigrants decided to go to a country open to receiving them (Agersnap et al., 2020).

### 2.2. The Peruvian Labor Market and Lima-Callao Economic Features

Most of Peru's labor force exists in the informal sector. Using a broad definition of informality as *those without employer health coverage or working at a small firm,* 72% of Peruvian workers are considered informal (INEI, 2018b). Peru's informal sector, overall, is above the regional

[8] The capital of Ecuador is an intermediate point with a distance to Caracas (Venezuela) of 1,089.34 miles. Yet, Ecuador received less than half of the number of immigrants that migrated to Peru (see Figure A.1.).
[9] For details on the working permit in Peru about the eligibility and changes since 2017, see Appendix C, which also includes a comparison with Colombia and the US immigration policies. For references to a similar immigration policy for the Venezuelan refugees in Colombia, see Bahar et al. (2021), Ibánez et al. (2020), Olivieri et al. (2020).

average of 53.8% when compared to other countries in Latin America, but is behind Bolivia at 83% and El Salvador at 79% (OECD/ILO, 2019). Additionally, the Peruvian labor market in Lima and Callao provinces, the country's largest metropolitan area, is relatively low-skilled. More than 50% of the working-age population in Lima and Callao neighborhoods has a high-school degree or less (INEI, 2019a). Moreover, among those in the informal sector, only 20% of the Peruvian workers in the informal sector have some years of superior education or university degrees (INEI, 2018b). Thus, the labor market in the destination country is mainly characterized by low-skilled workers in the informal sector.

Regarding the economic characteristics of Lima and Callao, there are two crucial features. First, during the 2010s, the economic growth of Lima and Callao and the whole country slowed. To illustrate, Lima and Callao provinces went from a 7.7% growth rate in 2010 to 2.1% in 2017 (see Figure A.2.). Secondly, the three most important economic activities in the informal sector are agricultural and mining activities, commerce, and other services (INEI, 2018b). Thus, it is less probable that a labor demand in a district from one specific economic sector of Lima and Callao has driven the large immigration influx since 2017.

Given the context of a large informal sector and positive slow economic growth, one might expect that the working permit for Venezuelan-born workers might have helped them find formal jobs under the Peruvian labor regime. However, according to recent reports from INEI (2019b), only 50% of Venezuelan immigrants in Peru applied for working permits, and 88.5% of employed Venezuelans were working without any legal contract. Thus, even with the favorable immigration policy offered by the Peruvian government, the opportunity to find a job in the informal sector is a potential determinant of the Venezuelan decision to migrate to Peru.

## 3. Empirical Strategy

In this section, I present the research design used to estimate the effect of the Venezuelan influx on Peruvian working-age population labor market outcomes. First, I start with a naïve specification and discuss the selection of immigrants into locations that confounds the estimates. Next, I present a difference-in-difference approach and event-study specifications. Finally, difference-in-difference research design assumes parallel trends in outcomes, so I discuss the threat to identification and when this assumption is violated.

### 3.1. The Naïve Model and the Selection of Immigrants into Location

In this subsection, I give an overview of the ideal case to study the effect of immigration on the local labor market and the problems that may arise in estimating the true impact of migration.

Using a naïve model to study the effect of Venezuelan immigration on the local labor outcome is calculated through:

$$y_{idt} = \beta Share_{dt} + \lambda Z'_{idt} + \gamma_t + \phi_d + \varepsilon_{idt} \qquad (1)$$

Where $y_{idt}$ is the Peruvian labor employment or wages, $Share_{dt}$ is the share of Venezuelan immigrants relative to the working-age population in district $d$ quarter $t$, $Z'_{idt}$ is the control vector with individual characteristics, $\gamma_t$ and $\phi_d$ are the time and districts fixed effects, and $\varepsilon_{idt}$ is the individual idiosyncratic error term. In an ideal experiment, where the immigrants are randomly located in a destination country, then the share of immigrants $Share_{dt}$ would be uncorrelated with any idiosyncratic shock in that district $\varepsilon_{idt}$. Formally, this is represented by $Share_{dt} \perp \varepsilon_{idt}$. In that ideal situation, $\beta$ would estimate the average effect of receiving a 1 percentage point increase in the share of immigrants on the Peruvian labor outcome.

The econometric challenge arises through immigrants deciding to migrate to places with more opportunities. This endogeneity is also known as *moving to opportunity bias*, where immigrants choose to move to a destination country based on two dimensions, (1) a city's characteristics and (2) employment demand in the local labor market (Altonji & Card, 1991; Borjas, 2003; Card, 2001; Kleemans & Magruder, 2018). A city becomes more desirable when wages are higher than other cities, which is a type of selection in levels. In other words, immigrant workers locate into places with better-paid jobs. Similarly, cities with increasing demand denote a selection bias in trends (Borjas, 2003). Intuitively, the increase in job vacancies is the main driver of immigrant decisions on where to locate. This location bias can over or underestimate the true effect of immigration on labor market outcomes depending on the type of immigrant worker skills and labor demand changes that drive immigration decisions.

### 3.2. Difference-in-Difference strategy

I use a difference-in-difference approach that exploits spatial variation of high exposure to the inflow of Venezuelans across the neighborhoods of Lima and Callao. Instead of using the level of immigration relative to each district's labor force, I compare districts with changes in the share of Venezuelan immigrants significant enough to reflect an unexpected influx of immigrants. Thus, the simple *difference-in-difference* model is as follows:

$$y_{idt} = \beta shock_d \times post2017_t + \lambda Z'_{idt} + \gamma_t + \phi_d + v_{idt} \qquad (2)$$

Where $y_{idt}$ is the Peruvian labor employment or wages, $shock_d$ is the net inflow of Venezuelans between 2016 to 2018 into district $d$, $post2017_t$ is a time dummy that takes 1 after January 2017, when the influx of immigrants started increasing, and the working permit was introduced to allow Venezuelan immigrants access to formal jobs. Similar to equation (1), $Z'_{idt}$ is the control vector with individual characteristics, $\gamma_t$ and $\phi_d$ are the time and district fixed effects respectively, and $v_{idt}$ is the individual idiosyncratic error term. The coefficient of interest $\beta$

estimates the impact of the unexpectedly high arrival of Venezuelan immigrants on Peruvian employment and wages after 2017.

### *3.2.1. Event-study Specification*

An event-study specification is informative of changes over time in the slope between the Peruvian labor outcome and the immigration net inflow. The following event-study specification estimates the differences in the slope over time:

$$y_{idt} = \sum_{\tau \neq 2016q4} \beta_\tau shock_d \times \mathbb{I}[\tau = t] + \lambda Z'_{idt} + \gamma_t + \phi_d + \mu_{idt} \qquad (3)$$

Where $\mathbb{I}[\tau = t]$ is a dummy that takes 1 by quarter and the baseline is the differences in outcomes in the fourth quarter of 2016. Equation (3) allows estimating the short-run effect of the net Venezuelan immigrant influx on employment and wages by quarter relative to 2016 quarter 4. Thus, the coefficient $\beta_\tau$ captures the effect of a 1 percentage point increase in the immigration shock on the Peruvian workers' labor market outcomes in $\tau$ versus the fourth quarter of 2016. I use this quarter and year as the baseline because of the immigration policy that provides Venezuelan-born immigrants a working permit starting in January 2017 (see section 2.1). Additionally, in comparison with the estimates of the difference-in-differences specification in equation (2), using 2016q4 as the baseline is equivalent to the time dummy $post2017_t$ that takes 1 since January 2017. Thus, I choose one time period before capturing the pre-treatment baseline to capture any immediate short-run effects.

### *3.2.2. Assumptions and Thread to Identification*

The *difference-in-difference* empirical strategy relies on the parallel trend assumption. The assumption states that outcomes for treated districts would have moved parallel to those in non-treated neighborhoods. In my case, the districts that received a larger share of Venezuelans are in the treatment group, and districts with more minor changes in the share of incoming Venezuelans act as control units.

The event-study estimates in equation (3) allow for checking the parallel trend assumptions before the large inflow of Venezuelan immigrants starts in 2017, which is the baseline of comparison. A selection in trends explained in section 3.1 would be a possible threat to identifying causal effects under this diff-in-diff approach. This selection would violate the parallel trends assumption, as the trends in potential outcomes for treated and control districts would differ. For example, this selection bias could exist if labor demand changed differentially across districts over the study period. Thus, the event-study estimates provide evidence of a violation of the assumption when there are positive or negative pre-trends. Additionally, the district fixed effects in equations (2) and (3) account for potential selection in level. Thus, this selection should not be a concern for identification.

From section 2, we have two main institutional backgrounds with qualitative evidence to support the empirical strategy and the parallel trend assumption for identification. First, the Venezuelan crisis contributed to the plausibly exogenous spatial variation of the labor supply due to the Venezuelan arrival in Peru. The latter means that the situation in Venezuela, discussed in subsection 0, is not correlated with the specific labor demand changes in one neighborhood within the metropolitan area of Lima and Callao. Second, the provinces of Lima and Callao experienced positive growth before the Venezuelan influx but at a slower pace (see Figure A.1). Thus, it is less probable that the economic growth driven by a change in the labor demand by district affected immigrant decisions on where to locate. Overall, it is more plausible that immigrants look for better life opportunities in Peru than for specific job demands within a neighborhood in Lima and Callao.

## 4. Data

This section describes the data sources, the variable construction, and the analytical sample used in estimation. I also document the Venezuelan influx in Lima and Callao and its features at the neighborhood level.

### 4.1. Data Sources

I study the effect of immigration on local worker employment and weekly wages as the primary labor market outcomes of interest. To estimate this effect, I combine two primary data sources. First, I use a unique data source, "*Survey of the Venezuelan population that lives in Peru*" (ENPOVE in Spanish) from the National Institute of Statistics and Information (INEI, 2018b). This survey was conducted in December 2018 across Peru, covering the five most populated provinces, 3,713 households, and 9,868 individuals.[10] In particular, I use information about the arrival date to Peru to construct the total number of Venezuelan migrants by quarter and neighborhood using survey weights. Using the arrival date of immigrants implies that I assume that Venezuelans do not change jobs since they arrived. Regarding the commuting across neighborhoods, the Venezuelan Survey (ENPOVE) on where they live and work. 2,062 of Venezuelans commute to other districts within Lima and Callao, this represents 26% of the Venezuelan sample. Thus, I assigned those that commute to the districts where they work. The rest of the Venezuelans work where they live.

Second, the Peruvian Labor Force Survey (LFS) contains the labor outcomes of interest, such as wages and employment since 2001 (INEI, 2022). The dataset is a quarterly survey made up of individuals, half of whom are surveyed for two consecutive quarters. The geographic unit of this

[10] In Figure A.3. shows the spatial distribution of Peruvian and Venezuelan populations in the whole country in 2019. Although the Venezuelan survey includes other provinces such as Tumbes, La Libertad, Arequipa, and Cusco; 60% of the sample belongs to Lima and Callao as shown in the largest orange circles in Figure A.3.

survey is a conglomerate that contains between three to five blocks, and each quarter consists of a total of 400 conglomerates. The survey covers the 43 districts in Lima and the 6 districts in Callao. The sample size is 4,800 households, with around 15,000 individuals in each quarter.[11] I focus on the data between 2014 and 2018 to estimate the effect of immigration. The LFS interviews only Peruvian households surveying for individual characteristics, and focuses on employment and unemployment information.

In this study, I estimate the effect of immigration on local labor markets at the neighborhood level. Throughout, the terms district and neighborhood will be used synonymously. For this estimation, I merged these two publicly available datasets by district level using a crosswalk between conglomerates and districts provided by the Peruvian National Institute of Statistics (INEI).

## 4.2. Variable Construction

In this subsection, I present the construction of the immigration shock and how I measure Peruvian employment and wages.

### *4.2.1. Immigration Shock Definition*

I use the spatial variation of the net inflow of Venezuelan-born immigrants as a plausible exogenous variation. First, I measure the number of Venezuelan workers relative to the 2017 working-age population in the neighborhoods of Lima and Callao by quarter. This measure is an intensity of treatment variable following Cascio & Lewis's (2019):

$$Share_{dt} = \frac{Venezuelan\ immigrants_{td}}{Population\ 14-\ 65\ years\ old_{d\ 17}} \qquad (4.a)$$

[11] The refusal rate of the LFS is 7.3% and remained constant between 2014 and 2018.

Where $Venezuelans_{dt}$ is the total number of Venezuelan migrants in district $d$ quarter $t$ from the Venezuelan Survey (ENPOVE), and $Population\ 14-65\ years\ old_{d\,17}$ is the working-age population between 14 and 65 years old in district $d$ in January 2017. The denominator only includes the Peruvians and the Venezuelans from both datasets, the Venezuelan Survey (ENPOVE) and the Peruvian Labor Force Survey (LFS), respectively. I fixed the denominator as the "pre-treatment" time before the large inflow arrives in Peru, as suggested by Card & Peri (2016). I use this quarter as a baseline to be consistent with the timing of the introduction of the working permit policy for Venezuelans in January 2017, coinciding with the start of the migration phenomenon to Peru, as discussed in the institutional background section 2.2.

I use the above share of Venezuelans in two ways. First, for the naïve estimation of equation (1), I exploit the availability of the Venezuelans' share by quarter and districts from the data sources described above. Second, to estimate specification (2), I use this time-varying share of Venezuelans to define continuous and discrete measures of the unexpected immigration shock. The continuous measurement of the net inflow of immigrants is the change in the share of Venezuelan immigrants between the fourth quarter of 2016 and the third quarter of 2018. If any district in 2016 has a missing value in the share of Venezuelans, I assume the value is zero.[12] This net inflow of immigrants mitigates potential inflation of the effect on wages due to omitted bias problem when using an immigration shock measure that considers the immigrants' arrival in the last 12 months (Lebow, 2022). Formally, I exploit the immigration shock at the district level as follows:

$$continuous\ shock_d = \Delta share_{d18} = share_{d18} - share_{d16} \qquad (4.b)$$

[12] In Appendix D, I show the number of districts with the quarterly share of Venezuelans in Table D.1. I also show that the probability of missing values in those districts is not correlated with the district characteristics in Table D.2.

The discrete measure of immigration shock captures high-exposure districts. It considers those with the most significant increase in the share of Venezuelan immigrants between 2016 and 2018. Formally:

$$discrete\ shock_d = \begin{cases} 1 & if\ \Delta share_d > p75 \\ 0 & otherwise \end{cases} \qquad (4.c)$$

This discrete definition of immigration shock has the advantage of a more straightforward interpretation using treated and untreated terminology (Angrist & Pischke, 2009; Cunningham, 2021). The districts with the most significant changes in the net inflow of immigrants are part of the treated group, which captures the right tail distribution of the net influx of Venezuelans.

### *4.2.2. Peruvian Labor Market Outcomes*

I study the effect of immigration on two primary labor market outcomes: employment and wages. First, I define the employment variable as equal to 1 when the respondent declares to have a job and zero otherwise.[13] To measure weekly wages, I combine the information on labor income from their primary job and the frequency of payments to homogenize everything into weekly income units. For example, monthly payments were divided by four, while daily income was multiplied by five.[14] Then, I deflate the total income variable using the CPI index to 2018 Peruvian currency *sol*. Finally, I converted them into December 2018 *US dollars* using the nominal exchange rate from the Central Reserve Bank of Peru.

To understand which group of Peruvian workers are most affected by the labor supply increase, I study the impact of immigration by sector and skills. First, I use a broad definition of the informal sector that identifies individuals that belong to either category: (1) without health insurance, (2)

[13] I use the variable "OCU200" in the LFS takes 4 possible categories: 1=occupied, 2=unemployed uncovered, 3= fully unemployed, 4= outside the labor force (INEI, 2022).
[14] I do not use the reported hours to obtain the hourly wages to minimize measurement error from both responses, income and hours worked.

belonging to a small firm size with ten or fewer employees, and (3) self-employed (INEI et al., 2017; Maurizio, 2014; Tornarolli et al., 2014; Ulyssea, 2018).[15] Second, I define low-skilled as those with a high school diploma or less and high-skilled as those with higher educational attainment than a high school degree. As a result, I observe an even distribution between the low and high-skilled Peruvian working-age population.[16]

### 4.3. Analytical Sample: Peruvian-born Labor Force Characteristics

The estimations focus on the effect of immigration on the Peruvian population that can potentially compete with the Venezuelan workers in the labor market. I restrict the sample to the Peruvian and Venezuelan population between 14 and 65 years old. With this restriction, I disregard whether they are employed, unemployed, or not actively looking for a job. I do not restrict the sample to those participating in the labor market, dropping the inactive population, because the estimates of the effect of immigration might mask changes in the sample restriction. For example, suppose the labor force participation decreases after the influx of immigrants, as in the case of Turkey (Tumen, 2016). Then, the sample of Peruvians used to estimate the effect of immigration on employment will overestimate the true impact of immigration because the Peruvians in the labor force sample will be smaller. Therefore, to avoid selection sample bias, I consider every respondent with the potential to participate in the Peruvian labor market.

I report Peruvian-born characteristics from the analytical sample and the mean differences before and after the 2017 immigration in Table 1. Based on the Peruvian individual and household characteristics, the salient statistical differences are age, time in their current job, and household

[15] The first and second categories overlap almost 100%. As a result, the first two definitions identify the same informal workers on average.

[16] The wage inequality literature distinguishes between high school dropouts and those with high school degrees to define skill levels (Card, 2009; Kleemans & Magruder, 2018). It is worth clarifying that I am not controlling for differences in educational quality between domestic and foreign workers (Card, 2009), because of differences in the educational systems between workers.

size. These average differences are consistent with time-variant individual and family characteristics. The quarterly time-fixed effect $\gamma_t$ from specification (2) consider this trend and any potential seasonality component in the outcome of interest (Angrist & Pischke, 2009; Cunningham, 2021). Therefore, the time variation in the working-age population should not be of concern when estimating the effect of immigration on local labor market outcomes.

Table 1 also shows that most of the Peruvian working-age population is in the informal sector, and two-thirds are low-skilled.[17] Overall, the table reports no significant changes in these labor market characteristics before and after the unprecedented Venezuelan-born immigration. These mean differences are relevant because they provide supporting evidence of the parallel trend assumption for estimating specification (2). To illustrate, suppose there is a labor demand increase in the formal sector in low-immigration districts only, which incentivizes Peruvian workers to switch from informal to formal in those areas. Then, the estimates of the effect of immigration on wages in the low-immigrantion district will have a different trend than in the high-immigrantion neighborhoods. Thus, this labor demand shock that affects the Peruvian workers' decision on the economic sector would violate the parallel trend assumption in that case. For these reasons, Table 1 shows suggestive evidence that no average statistical differences in the informal sector or skills composition could violate the identification assumption of specification (2).[18]

[17] The reported 55% in the table is smaller than the 72% labor informality mentioned earlier in the text (INEI et al., 2017). This difference is due to my sample restriction considering the working-age population, while the latter percentage considers only those participating in the labor force. If I include only the individuals that are employed and unemployed, 65% of the labor force is in the informal sector. Further, remember the sample covers the Lima and Callao metropolitan area, where the informality level is smaller than in rural areas (OECD/ILO, 2019). For these reasons, my estimate of labor informality is only 7 percentage points less than the 72% mentioned in this paper.

[18] In Figure A.4, I show no trend difference in Peruvian employment and wages either in the formal or informal sector between 2014 and 2018. Further, in Figure A.5, I plot the raw employment and wage trends by broad skill definition within each economic sector in Lima and Callao. Overall, there are no qualitative trend differences between the formal and informal sectors, nor between low- and high-skilled Peruvians within sectors.

Finally, I compare the labor market outcomes pre- and post-immigration shock in Table 1. It is worth noting that there are no statistical differences in the probability of being employed in contrast with a significant statistical difference in weekly wages. The increase in wages after 2017 might reflect an increase in the productivity of employed workers, which is reasonable in a context with a positive economic growth rate. However, the simple before and after comparison does not consider what happened with salaries in low versus high-immigrantion neighborhoods. For these reasons, the difference-in-difference approach provides an intuitive estimation of the effect of immigration on local labor market outcomes under the parallel trends assumption.

## 4.4. Venezuelan Immigration Characteristics

In this subsection, I document Venezuelan inflow characteristics at the neighborhood level in the Lima-Callao metropolitan area.

### *4.4.1 Time and Spatial Variation of the Venezuelan Inflow*

I present the time and spatial variation regarding the influx of Venezuelan immigrants in the neighborhoods of Lima and Callao provinces between 2016 and 2018 in Figure 1. Panel (a) shows the aggregate share of Venezuelans define in (4.a). Venezuelan immigrants represented more than 6% of the 2017 working-age Peruvian and Venezuelan populations in Lima and Callao, where most of the increase happened during 2018. This extraordinary increase in the inflow of immigrants is consistent with the changes between February and April 2018 in ranking destination countries for Venezuelans documented by UNHCR & IOM (2022).

I show the geographic location of Venezuelan immigrants within the provinces of Lima and Callao by year in panel (b). The left-to-right panel shows the years from 2016 to 2018 Venezuelan immigrant waves. These maps show that recent Venezuelan immigrants locate across districts with a higher share of Venezuelans in earlier years (Altonji & Card, 1991; Monras, 2020). However, in

2016 the share of Venezuelans ranged between 0.00% and 0.48%, while in 2018, it ranged from 8% to 31%. Thus, panel (b) shows the first qualitative evidence that the Venezuelan-to-Peru immigration in Lima and Callao do not have enough variation in past settlements to use as an instrument in an IV approach (see Section 6).

To study the effect of the immigration boom on the metropolitan area of Lima and Callao, I use the changes in this share of Venezuelans as the immigration shock. Recall that in section 4.2.1, I define a continuous and discrete measure of the immigration shock. Figure 2 presents the distribution of changes in the share of Venezuelans between 2016 and 2018, as illustrated in equation (4.a). On average, the net inflow of immigrants is 0.08, starting from 0.001 in the neighborhood "Mi Peru" to 0.30 in the "San Luis" district. The district "Magdalena del Mar," with a net change of 0.11, is the percentile 75 of the net inflow of immigrants distribution. The average immigration shock for districts above the 75$^{th}$ percentile is 0.19, and the maximum change in the share of Venezuelan immigrants is 0.30 in "San Luis" district. Thus, all the districts above 0.11 have the highest Venezuelan immigration influx treated in the discrete measure of shock.

Two advantages stand out from the continuous shock measure. First, it exploits the spatial variation across neighborhoods and provides an average intensity-to-treatment effect to the net inflow of Venezuelan immigrants. Second, this change in the share of Venezuelan immigrants accounts for trends in immigration flow. As Jaeger et al. (2018) suggest, the prediction of immigrant locations using spatial variation in the past might suffer spurious autocorrelation when it is closer in time and without changes in immigrant shock composition. Thus, this measure does not rely on the past distribution of Venezuelan immigrants across Lima and Callao neighborhoods to determine the most recent inflow.

### *4.4.2. What are prominent immigrant worker characteristics?*

I characterize the Venezuelan influx in Lima and Callao neighborhoods. Understanding immigrant characteristics is relevant because the immigration shock represents a shift in labor supply within the labor market, and it helps understand the local labor market response. Further, it also adds evidence in favor of the identification strategy to estimate the effect of immigration on the Peruvian labor market employment and wages.

The first salient feature of Venezuelan immigration is the means of transportation from their country to Peru. Figure 3 shows that 84.7% of the working-age sample that live in Lima and Callao arrived by plane.[19] This fact suggests that the influx of Venezuelans is unexpected by the Peruvian labor market. It is less probable to predict how many additional new Venezuelan immigrants will arrive in their neighborhoods when the immigrant influx does not have a long trip through other countries, like Ecuador. Further, the plane signals that the type of immigrants must be at least medium and high-income Venezuelans since they are able to afford plane tickets from Venezuela to Peru.

Regarding the characteristics of the immigrant inflow, in Figure 4, I present three facts about this large influx to Peru. First, in the top panel, I show that 75% of Venezuelan immigrants are of working age (15-65), meaning that most of the immigration influx will affect the local labor market. Second, among those of working age, 87.5% of the Venezuelan respondents do not have any legal contract, meaning they belong to the informal sector, as shown in the bottom left panel (a). Finally, from the bottom right panel (b) notice that 57% of Venezuelan-born immigrants have

[19] The Venezuelan Survey has information on the month and year they left their country and the arrival date. With this information, I constructed a time travel variable in months. Table B.1. shows that the travel time is consistent with most of them arriving in Peru on a plane.

a high-school degree or less.[20] Compared with the Venezuelan-born immigrants that went to Colombia, the ones that went to Peru are relatively more educated because 26.9% of Venezuelans in Colombia have more than a high school degree (Santamaria, 2020a). Venezuelan immigrant characteristics are further explored in Table B.2. The relevant features noted in 2018: Venezuelans are more likely to be younger single male immigrants with lower education attainment than in 2017. In summary, Venezuelan-born immigrant characteristics suggest that the immigration shock will translate into an increase in the informal sector labor supply.

### *4.4.3. How Do Neighborhoods with Higher Immigrant Influx Look?*

I explore the characteristics of the neighborhoods that received most of the Venezuelan influx. In Table 2, I present the labor market characteristics, economic characteristics, individual Peruvian working-age characteristics, along with household features before 2017 for low and high-immigrant neighborhoods. High-immigration neighborhoods are defined as the discrete immigration shock in equation (4. b). The high-immigration dummy takes a value of one when the change in the share of Venezuelans in a district is above the 75th percentile of Venezuelan net inflow. In this case, we take the immigrant distribution between 2016 and 2018. Before the influx of Venezuelans occurred, the neighborhood with the highest exposure to Venezuelans had higher employment rates, lower-paid jobs, and fewer formal firms, consistent with poorer districts. These places, with a large net inflow of Venezuelan immigrants, also have a relatively low-skilled labor force.

[20] In Figure A.3, I show the time and spatial variation of the immigration shock by skills. The top panel shows that between 2016 and 2018, the inflow of Venezuelans is evenly distributed between low- and high-skilled, and only in the last two quarters of 2018 the share of low-skilled workers increases. The bottom panel suggests there is no qualitative evidence that Venezuelan immigrants sort across neighborhoods depending on their skill types. See also Table B.2. with similar distributions of Venezuelan observations across Lima and Callao by skills. Therefore, I do not use this measure of the influx of Venezuelans by skill to estimate the effect of immigration on local labor market outcomes.

# 5. Results

This section presents the results of the effect of Venezuelan influx on employment and weekly wages for Peruvians in Lima and Callao between 2014 and 2018. I also show the event-study plots to provide suggestive, yet imprecise, evidence that the parallel trends assumption has not been violated. I then show the heterogeneous analysis separated by low- and high-skilled Peruvians in the informal and formal sector.

## 5.1. Difference-in-difference Estimations

This subsection focuses on the difference-in-difference estimation of the effect of Venezuelan influx on Peruvian employment and weekly wages. Although the event-study estimations have large standard errors, the difference-in-difference results are driven by the 2018 quarters. Finally, I provide evidence of the labor market response differences between workers in the informal and formal sectors.

### *5.1.1. Effect of Venezuelan Influx on Peruvian Employment and Weekly Wages*

I provide evidence of the recent influx of Venezuelan immigrants on the Peruvian labor market outcomes in Table 3. I present the estimates for the probability of being employed and the natural log of weekly wages in panels A and B, respectively. The table compares the difference-in-difference estimates of the naïve OLS specification (1) discussed in section 3.1, and the two measures of the immigration shock variables. In panel A, the first column using the time-varying share of Venezuelans in equation (4.a), shows that the coefficient of the quarterly share of Venezuelans on Peruvian-born employment is indistinguishable from zero. This share of Venezuelans does not capture the unpredictability of immigrant settlement in each district as the immigration shock defined in section 4.2.1. If there is an increase in labor demand increase in one district that increases the share of Venezuelans and Peruvian employment, then the naïve OLS estimates will be bias upward.

The estimate of the effect of continuous immigration shock on Peruvian-born employment (shown in column (2)) is equivalent to the discrete shock measure in column (3), despite the continuous measure being six times larger than the discrete measure. Recall that the discrete measure is a function of the continuous measure – see section 4.2.1.[21] The statistical interpretation of the continuous shock is that an increase of the net inflow of Venezuelans by 1 percentage point increases the average employment rate by 0.12 percentage points.[22] In contrast, the discrete shock offers a more direct casual interpretation under the parallel trends assumption. On average, the high-immigration neighborhoods experienced a 2 percentage point increase on the employment probability relative to low-immigration areas.

The point estimate of the influx shock on the employment is relatively small for the Peruvian labor market in Lima and Callao. From Table 3, the average employment rate in high-immigration neighborhoods is 0.74. This means that for a 2017 Peruvian-born working-age population of 7.6 million in Lima and Callao, 5.6 million are employed (INEI, 2019c). Then, the 2 percentage point increase in the employment rate implies that 112,480 Peruvians in the working-age population are employed in the high-immigration districts after 2017.

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[21] The average difference of the continuous immigration shock between districts above and below the percentile 75 is 0.15. Thus, after 2017, a 15 percentage point increase of the continuous net inflow of Venezuelans increases the probability of being employed in 2 percentage points. Formally, from equation (2):
$\Delta P(Employed) = \beta \Delta shock_d \times post2017_t$, replacing the estimate, the change in the share, and $post2017_t$=1
$\Delta P(Employed) = 0.12 \times 15 = 1.8 \approx 2$
Thus, the two measures capture equivalents effect of the immigration shock on the Peruvian-born employment.

[22] In the general, case for the level-level regression: $y = \alpha + \beta x + \epsilon$ the statistical interpretation of the coefficient $\hat{\beta}$ is: if we change $x$ by one unit, then we would expect $y$ to change by $\hat{\beta}$. Formally, $\Delta y = \hat{\beta} \Delta x$.
Recall the difference-in-difference specification is:

$$y_{idt} = \beta shock_d \times post2017_t + \lambda Z'_{idt} + \gamma_t + \phi_d + v_{idt} \qquad (2)$$

Replacing the variables in this case, the formal interpretation of the coefficient $\beta$ is: $\Delta Prob(Employed) = \beta \times \Delta(\Delta share)$. Now, an increase in 1 unit of the continuous immigration shock means $\Delta share = 0.01$, while a 1 percentage point increase of this shock is $\Delta share = 0.01 \times 100$. Thus,

$$\Delta Prob(employed) = 0.12 \times 0.01 \times 100$$
$$\Delta Prob(employed) = 0.12$$

The effect of the Venezuelan immigration on weekly wages of the Peruvian working-age population is negative as shown in panel B Table 3. First, the naïve OLS estimation of the share of Venezuelan-born by quarter and district on weekly wages shows a positive and significant association. However, the difference-in-difference estimation of the immigration shock on the weekly wages presents a negative coefficient. Thus, the OLS estimate sign suggests that the positive trend of the level in the share of Venezuelan to working age population might generate this positive bias of the effect of immigration that offset the negative effect, and it can be a spurious positive correlation (Jaeger et al., 2018b).

Similar to employment estimates, the wage regression using continuous shock is equivalent to the discrete measurement of the effect of immigration. In panel B of Table 3, Column (2) indicates that a 1 percentage point increase in the continuous change of the share of Venezuelan immigrants reduces the weekly wages of the Peruvian working-age population by 0.20%.[23] Since the average change of the share of Venezuelans is 0.08, then this estimate implies the mean reduction in weekly wages across all neighborhoods is 1.6%. The discrete shock measure in Column (3) shows that the Peruvian-born working-age population in high-immigration districts have 2% less weekly wages than those in low-immigration areas. Since average weekly wage is 230 USD 2018, the 2% weekly wage reduction is equivalent to USD 4.6 less.

The results of the Venezuelan immigration influx on Peruvian employment and wages in the provinces of Lima and Callao are consistent with previous studies in Peru. Regarding employment,

[23] The log-level regression: $\log y = \alpha + \beta \times x + \epsilon$ has the following formal interpretation of the coefficient: $\%\Delta y = 100 \times \hat{\beta} \times \Delta x$. In words, a 1 unit increase of x increases y in $\hat{\beta}\%$. Thus, in my case, using specification (2): $\ln wage_{idt} = \beta shock_d \times post2017_t + \lambda Z'_{idt} + \gamma_t + \phi_d + v_{idt}$. The formal interpretation is as follows: $\%\Delta wage = 100 \times \beta \times \Delta(\Delta share)$. A 1 percentage point increase of the continuous shock is $\Delta x = \Delta share = 0.01$. Then,

$$\%\Delta wage = 100 \times (-0.20) \times 0.01$$
$$\%\Delta wage = -0.20\%$$

An 8 percentage point increase of the continuous shock is $\Delta x = \Delta share = 0.08$. Then,

$$\%\Delta wage = 100 \times (-0.20) \times 0.08$$
$$\%\Delta wage = -1.6\%$$

I find an increase in employment three times larger than Groeger et al. (2022), Denisse & Morales (2020) and Boruchowicz et al. (2021). In contrast to previous study at the national level by Vera & Jimenez (2022), I detect a negative effect on wages for the Peruvian working-age population in Lima and Callao districts. More importantly, I can rule out a negative effect on local employment and a significant reduction of wages larger than 5% in high-immigration neighborhoods. Therefore, my findings suggest that the labor market in Lima and Callao can absorb the 7.5% increase in labor supply due to the influx of Venezuelan-born immigrants between 2017 and 2018.

#### *5.1.2. Event-Study Estimations of the Effect of Immigration on the Peruvian Labor Market Outcomes*

Although the parallel trends assumption for casual identification is not directly testable, in Figure 5 and Figure 6, I show the event-study plots of equation (3) to provide suggestive evidence that the parallel trends assumption has not been violated from the pre-period to the large influx of immigration (Cunningham, 2021). The event-study plots on the differences of Peruvian labor outcomes show there is not enough precision to reject nor to not reject the null hypothesis of the parallel trends assumption before 2017. Comparing the continuous with the discrete measure of the immigration shock, the estimates of the effect of immigration on employment and wages are more precise using discrete shock. Even though the evidence is inconclusive, the point estimate coefficients oscillate around zero between 2014 and 2017.

One advantage of the event-study estimates is that they provide evidence of the quarters that drive the positive effect of employment and the negative effect on wages in the difference-in-difference estimates. First, the event-study estimates show a positive and significant effect on the Peruvian working-age probability of being employed in highest immigration neighborhoods in the third quarter of 2017 and the last two quarters of 2018 relative to the lowest immigration net inflow districts in the fourth quarter of 2016. Second, there is a clear negative effect on Peruvian-born weekly wages between the 1st and 3rd quarters of 2018 in high-immigration districts relative to low-immigrant districts in the fourth quarter of 2016.

Under a competitive labor model with the strong assumptions of perfect substitution of immigrants and natives, the increase on the local employment after the large immigration shock is consistent with a labor demand increase (Delgado-Prieto, 2022a). The labor demand in the Lima and Callao market might be explained by an increase in the demand for goods and services from immigrants themself in those districts. Thus, the average firm decides to hire the relatively cheaper input, labor units, after the decrease in wages, which implies that one should expect firms to increase their production size or scale.

#### *5.1.3. Impact of Venezuelan Immigration on Peruvian-born Labor Market Outcomes by Formal and Informal Sector*

Most of the Peruvian labor force works in the informal sector, so I estimate the effect of the recent influx of Venezuelan-born on the Peruvian labor market outcomes by sector in Table 4. Column (1) to (3) shows the separate regression estimates for the Peruvian working-age population in the informal sector, while column (4) to (6) shows the estimates for the formal sector. First, notice that the naïve OLS estimation for the whole analytical sample in Table 3 hides the opposite sign of the coefficients by sector in column (1) and (4). A 1 percentage point increase in the share of Venezuelans is associated with 0.21 percentage points in the probability of being employed in the informal sector, while the effect on formal employment is negligible. Intuitively, these correlations are consistent with Table 2, which shows the mean differences between low- and high-immigration neighborhoods. Venezuelan immigrants settle in places with higher employment in the informal sector and fewer formal firms. Thus, under the trend caveat mentioned before, the naïve estimation of the share of Venezuelans in levels on the Peruvian probability of employment by sector goes in the expected direction.

I present the difference-in-difference estimates on employment in panel A in Table 4, in columns (2)-(3) and (5)-(6). Regardless of the immigration shock measure used, the effect of the Venezuelan inflow after 2017 on employment is not statistically different from zero in the informal sector in columns (2)-(3). Similarly, the positive effect on the probability of being employed is driven by the formal sector no matter which definition of shock I use, as shown in columns (5)-(6). Using the formal sector sample, there was a 2 percentage point increase in the probability of being employed in the highest immigration districts when compared to low-immigration locations. As discussed earlier, the increase in the demand for goods and services from the arrival of immigrants to Lima and Callao may have increased the labor demand after 2017 enough in the formal sector to increase the probability of employment for the Peruvian-born working-age population. In that case, the firm that hires both formal and informal sectors is increasing the demand for formal labor, suggesting a high degree of imperfect substitutability between Venezuelan workers and Peruvians that choose to work in the formal sector (Delgado-Prieto, 2022).

Based on the characteristics of the Venezuelan-born population analyzed in Section 4.4.2, it was reasonable to think the immigration shock translated into an expansion of the informal labor supply with a decrease in informal wages. With a 10% statistically significant level of confidence and the continuous immigration shock, I detect a large and negative effect of the labor supply shock on Peruvian-born weekly wages in the formal sector due to the Venezuelan immigration. With a 1-percentage-point increase in the continuous net inflow of immigrants between 2016 and 2018, Peruvian formal wages decreased by 20% on average. For an average formal weekly salary of 125 USD (in 2018), this is a reduction of $25 USD. In contrast, the standard errors are large compared to the point coefficient estimate for detecting an effect on informal wages. Thus, I can only rule out a reduction in informal wages above 24% with a 5% significance level.

## 5.2. Heterogeneous Analysis: Low and High-skilled Peruvian Workers within each Sector

In this subsection, I start providing evidence of the effect of immigration on employment separated by low- and high-skilled within sectors. First, Table 5 shows results of the net inflow of Venezuelan immigrants on Peruvian probability of being employed in the informal (columns (1) to (3)) and formal sectors (columns (4) to (6)), where Panel A shows the results for low-skilled workers and panel B for the high-skilled sample. Then, I present the difference-in-difference estimates of Peruvian weekly wages in Table 6, displaying the same pattern of informal sectors (columns (1) to (3)) and formal sectors (columns (4) to (6)), as well as Panel A and B which show results based on skill.

### *5.2.1. Peruvian Employment Response to the Influx of Venezuelan Immigrants by Skills within Sectors*

The positive effect due to the influx of Venezuelan immigrants on the Peruvian probability of being employed is driven by an imprecise positive effect on high-skilled Peruvians in both the informal and formal sector. The lack of evidence of the Venezuelan immigration impact on Peruvian employment in the informal sector as a whole is hidden in the composition of low- and high-skilled workers. In column (2), the low-skilled sample is more than two times the high-skilled sample in the informal sector, which is consistent with the relatively low-skilled informal sector as shown in Figure A.5. The imprecise estimate of the effect of immigration on informal employment for low-skilled Peruvians masks the positive and significant effect of employment in that sector for high-skilled Venezuelans. Using the continuous immigration shock definition, a 1 percentage point increase in the net inflow of Venezuelans between 2016-2018 increases the probability of being employed by 0.16 percentage points for high-skilled Peruvians in the informal sector. More importantly, I can *rule out* a negative impact on employment below -0.015 for low-skilled Peruvians in the informal sector. In other words, the Venezuelan influx does not crowd-out local employment for Peruvians worker with less than a high school degree that works in the informal sector.

Analysis by skill also reveals that the formal sector contributes to the positive effect of immigration on Peruvian employment rate for the whole sample. The probability of employment in districts with the highest immigration shock is 2 percentage points higher after 2017 than in districts with low immigration inflow (column (6)). This direction of effect on employment is not as expected under a competitive dual labor market with a minimum wage policy that restricts low-skilled salaries in the formal labor market (Kleemans & Magruder, 2018). Although these results for the formal sector have large standard errors using a discrete measure, I can rule out an effect of immigration larger than -0.017 on the probability of employment for low-skilled Peruvian workers in the formal sector.

The lack of evidence for low-skilled Peruvian employment and an increase in high-skilled local labor in both informal and formal sectors can be understood with the following economic interpretation. Under a competitive labor market model, where firms hire any type of skill combination, this result suggests that Peruvian and Venezuelan high-skilled workers might have a high degree of imperfect substitution. Similar to Ottaviano & Peri (2012), there might be comparative advantages for each type of worker as well as firm benefits from hiring Peruvian and Venezuelan employees. Further, the increase in high-skilled workers suggests a *scale effect* meaning that firms increased their size or production by hiring more immigrants and local labor inputs in Lima and Callao (Delgado-Prieto, 2022a).

#### *5.2.2. Peruvian Weekly Wages Response to the Influx of Venezuelan Immigrants by Skills within Sectors*

The negative effect of a large net inflow of immigrants on weekly wages is driven only by the low-skilled Peruvians in the formal sector. Low-skilled Peruvian workers in the formal sector in districts with the highest immigration see a 5% reduction in weekly wages than in low influx Venezuelan areas. This result is surprising because under a dual-labor market for the formal and informal sectors, and assuming a minimum wage policy that constrains low-skilled labor inputs, one would not expect a decrease in the market (Kleemans & Magruder, 2018). However, the last minimum wage policy in Peru set the formal wages at 68 US 2018 dollars, while the average low-skilled wage is $92 USD – as shown in Panel (b) Figure 5.A. and Table 6 columns (4) to (6) (Decreto Supremo Nº 004-2018-TR, 2018). Thus, the 5% reduction in low-skilled wages means a $4.6 USD loss for Peruvians in the highest immigration shock after 2017, which is still above the minimum wage.

The estimates of the effect of Venezuelan influx on Peruvian weekly wages by skills within the informal sector have lower precision. I cannot detect a statistically significant effect for low- and high-skilled Peruvian workers in the informal sector across the neighborhoods of Lima and Callao. However, for the low-skilled in the informal sector, columns (1) to (3), I can rule out negative effects of immigration larger than -4.2% and positive effects higher than 3.6%. By comparison, for high-skilled Peruvians, the effect of the highest immigration districts cannot reduce wages by more than 8.8% nor increase wages by more than 6.8%. Overall, these results are consistent with previous studies of Venezuelan immigration on Peruvian wages for the whole country except for Boruchowicz et al. (2021), which finds a reduction in Peruvian hourly wages by 20%. Other studies rule out negative effects of immigration on Peruvian salaries larger than -1.5% (Denisse & Morales, 2020; Gröger, 2021).

## 6. Discussion

In this section, I briefly discuss other research designs to estimate the effect of immigration on local labor market responses. The main econometric issue with evaluating the impact of immigration on local labor market outcomes is that the immigrants are the ones who decide where to locate. Typically, the immigration literature uses an IV approach, which exploits exogenous variation to predict immigrant locations and estimate the causal effect of immigration on wages and employment.

One instrument used to predict immigrant locations is the distance between the city of origin and destination, but this intuitive instrument is commonly used with countries that share a border (Baez, 2011; Becker & Ferrara, 2019; Caruso et al., 2019; Delgado-Prieto, 2022a; Maystadt & Verwimp, 2014). The reason to use distance is that cities in a destination country closer to an origin city should have a higher inflow of immigrants when they travel on foot or by car. However, in this setting, Peru and Venezuela are not neighboring countries. Further, most Venezuelan immigrants arrived by plane (see Figure 3), which implies that the argument used for the distance instrument is less likely to hold. Thus, I cannot exploit the distance between locations in Venezuelans and districts within Lima and Callao because these countries are not next to each other, and most immigrants arrive by plane.

In current immigration literature, it is common to use the networking idea where immigrants in the destination country influence the location of new immigrants (Adão et al., 2019; Altonji & Card, 1991; Borusyak & Hull, 2020; Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018a). The identification assumption of the IV research design is that the share of Venezuelans in the past is not correlated with current changes in the local labor market that affect Peruvian labor market outcomes and immigrant location decisions (Altonji & Card, 1991; Monras, 2020). In other words, under the exclusion restriction, this geographic distribution does not affect the current local labor market outcomes, meaning that one can estimate the causal effect of immigration on native employment and wages.

In Appendix E, I present a simple approach to estimating the inflow of Venezuelans in 2018 with the share of Venezuelans in previous years across neighborhoods following Monras (2020). Additionally, I use two different definitions of this shift-share instrument to measure the past settlement of Venezuelans. One measurement exploits the variation from the city of origin from the Venezuelan Survey (ENPOVE) following the shift-share definition outlined by Delgado-Prieto (2022) and Jaeger et al (2018b). The other definition uses the traditional enclave share with information from the Census in 2007 and 2017 (Card, 2009). However, all the different instrument candidates have a weak first stage in this case, with an F-statistic below 12. The reason for low prediction power in first-stage estimates is that there have been few Venezuelan migrants to Peru in the past that help to predict an extensive range of arrival to various neighborhoods in the metropolitan areas of Lima and Callao. The latter also shows that the spatial variation from the past is not enough, even in the provinces with the highest immigration influx relative to other locations in Peru.

## 7. Conclusion

This study investigates the impact of increased labor supply, due to a large immigration inflow, on Peruvian labor outcomes in a developing country. I exploit the spatial variation of the net inflow of Venezuelans across the neighborhoods of Lima and Callao and estimated the causal effect on

Peruvian citizens' wages and employment. Using this arguably exogenous Venezuelan inflow between 2016 and 2018 in a difference-in-difference approach, I find evidence of a positive effect of Venezuelan immigration on employment and a negative effect on Peruvian wages. After a heterogeneity analysis by low- and high-skilled workers within sectors, results indicate that the positive effect on employment is driven by the high-skilled Peruvian working-age population in both the formal and informal sectors, while the negative effect on wages is only explained by low-skilled Peruvians in the formal sector. My estimations of the effect of immigration are in line with findings from previous studies in similar settings and do not indicate displacement of local labor (Caruso et al., 2019; Delgado-Prieto, 2022a; Denisse & Morales, 2020; Groeger et al., 2022; Santamaria, 2020b).

The recent Venezuelan diaspora can shed light on the debate about the effects of immigration on the Peruvian labor market. Because the informal labor market in Peru represents around 72% of workers, exploring the effect of immigration in these two sectors adds to our understanding of the degree of substitutability between native and foreign skill groups within sectors. In contrast to Colombia, where the hiring of Venezuelan immigrants resulted in substitution of Colombian workers in the informal sector (Delgado-Prieto, 2022a), I find a complementary relationship between high-skilled Peruvian workers with the relatively high-skilled Venezuelan immigrants in the informal sector. These results contrast the theoretical prediction on substitutability for workers with similar skills but different nationality, suggesting a high degree of imperfect substitution between the local and foreign labor units.

The migration shock to the local labor market of Peru is an opportunity to learn about labor substitutability by sector and skills because Peruvians and Venezuelans share Spanish as their mother tongue. Language is relevant because in cases where immigrants do not speak the language of the country of destination, there is a high cost of communication and a lowering in workplace productivity (Dale-Olsen & Finseraas, 2020; Heller, 2014). One might argue that this language condition is similar to the internal migration context (Kleemans & Magruder, 2018). However, this setting has two nationalities with different accents and widely different historical backgrounds that decrease the degree of substitutability in the language dimension versus the country of origin.[24] Therefore, the degree of imperfect substitutability might contribute to understanding the use of different labor units in the production function with equal language but different accents and historical backgrounds (Borjas, 2003; Ottaviano & Peri, 2012).

The labor market structure provides an explanation for why I can rule out negative effects of Venezuelan immigration on Peruvian employment and wages. For example, in Colombia, negative effects on the overall market where Venezuelan immigrants participate in local economies are explained by food services, construction, and manufacturing sectors (Santamaria, 2020b). Similarly, While most Venezuelan immigrants work in these three same sectors in Peru (INEI, 2018a; Vera & Jimenez, 2022), Peruvian workers in those sector have the option to search for better paid jobs and switch occupation (Boruchowicz et al., 2021; Dustmann et al., 2017). Thus, local labor switching within the informal sector explains Peru's lack of evidence for a negative effect on informal employment and wages.

Although the competitive framework helps to understand the theoretical predictions of immigration on local labor markets, whether the results of my research are related to a labor market where employers have some market power could be addressed in future work. When there is monopsony power, the employer might pay wages that are lower than the market wages in a competitive market (Sokolova & Sorensen, 2021). A plausible mechanism for the reduction on

[24] A recent study finds that Venezuelans are more likely to be discriminated against in places with a larger informal sector in Peru (Groeger et al., 2022).

formal wages for low-skilled Peruvians is that firms in this sector have monopsony power and discriminate in favor of locals (Groeger et al., 2022; Hirsch & Jahn, 2015). To illustrate, one potential monopsony by district in the formal sector might be the public sector. Therefore, the effect of immigration across districts in one large local labor market can be rationalized with another theoretical framework.

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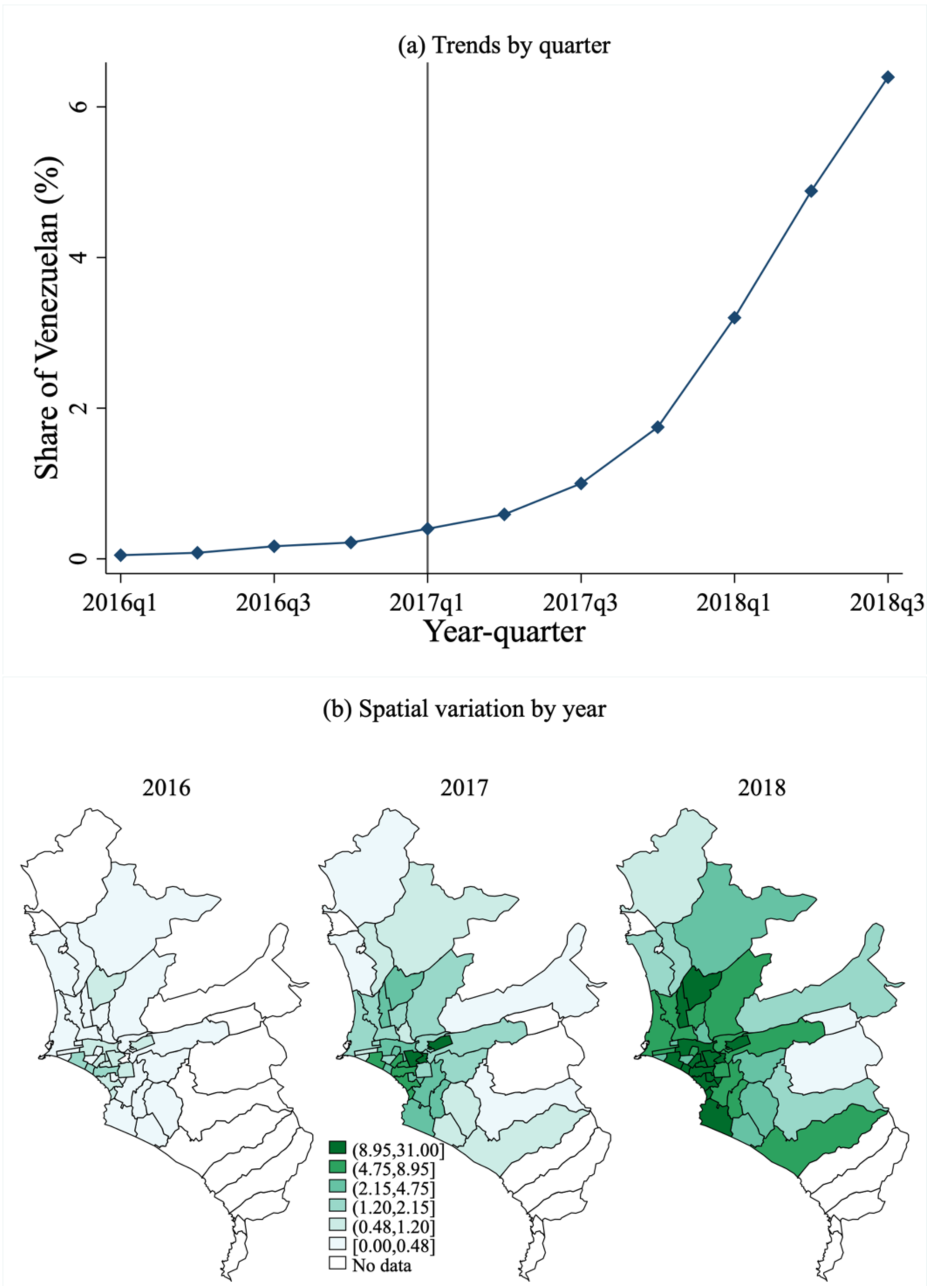
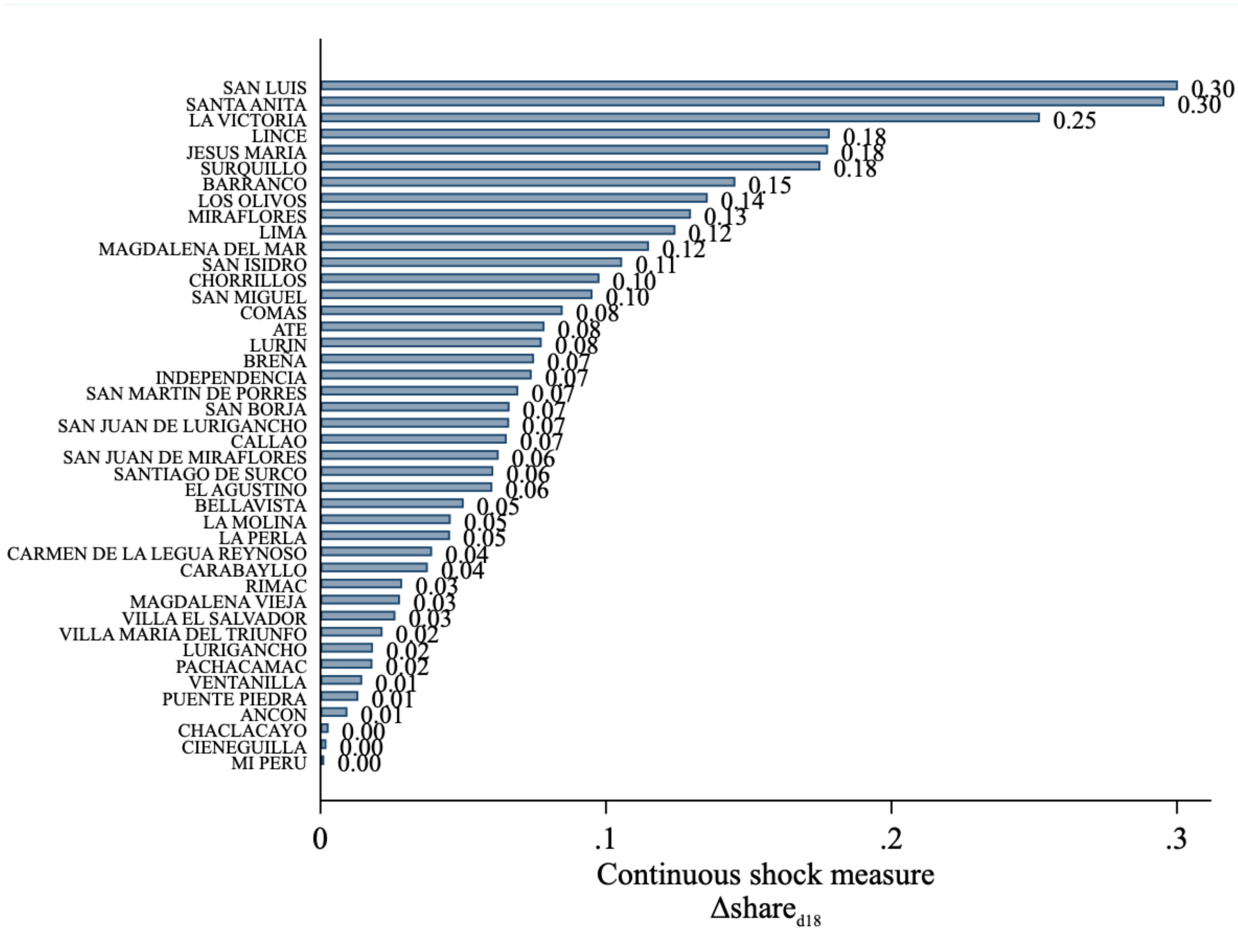
## Figures

**Figure 1. Time and spatial variation of the share of Venezuelan immigrants (in %) in Lima and Callao, 2016-2018**



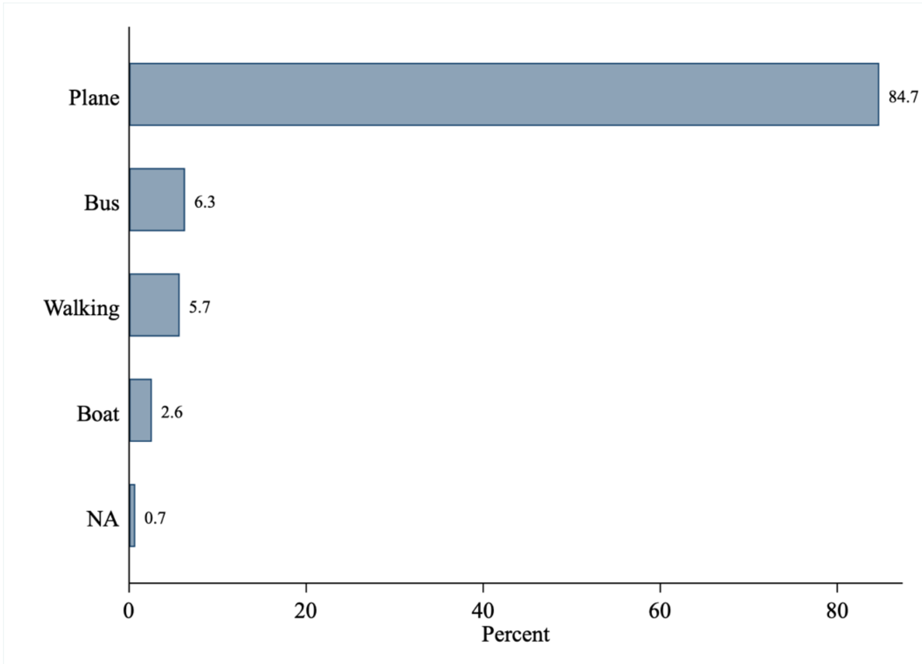

Note: These figures show the time and spatial variation of the influx of Venezuelans to Lima and Callao neighborhoods between 2016 and 2018. Panel (a) show the cumulative share of Venezuelans, defined as the ratio of the stock of immigrant-born to the population between 14 and 65 years old, in January 2017 (in %). The vertical gray line indicates the introduction of the working permit in January 2017, which is a legal immigrant status for Venezuelans. Panel (b) shows the share of Venezuelans in the Lima and Callao districts by year (in %).

**Figure 2. Distribution of the continuous measure of the immigration shock by districts in Lima and Callao**



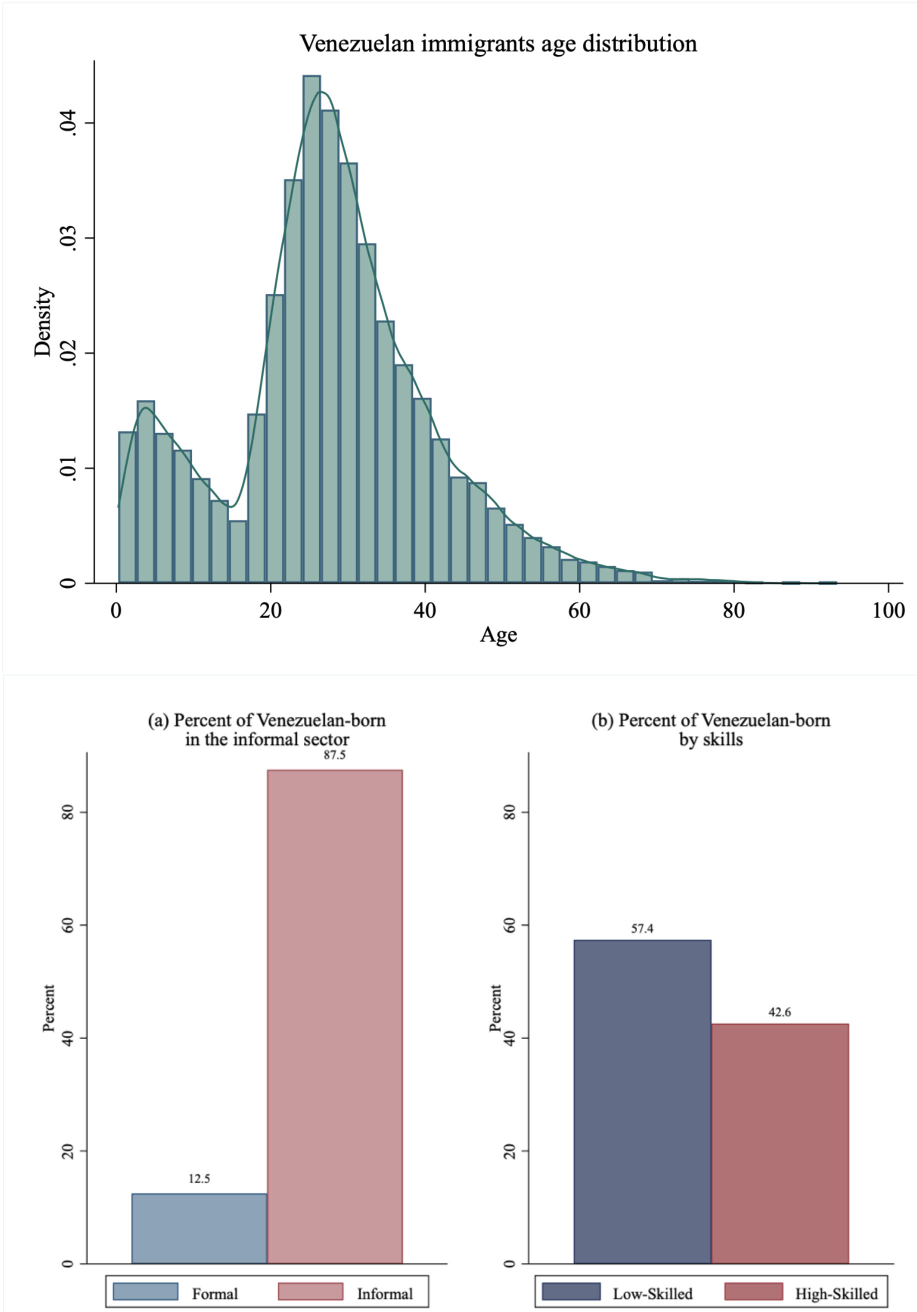

Note: This figure shows the net inflow of Venezuelans between 2016 and 2018. This shock is the continuous measure of the immigration shock defined as the change in the share of Venezuelans from the end of 2016 to 2018 (see equation (2.a)). The percentile 75 of this distribution is district Magdalena del Mar, with a net inflow of 0.11.

**Figure 3. Immigrant transportation mode from Venezuela to Peru**



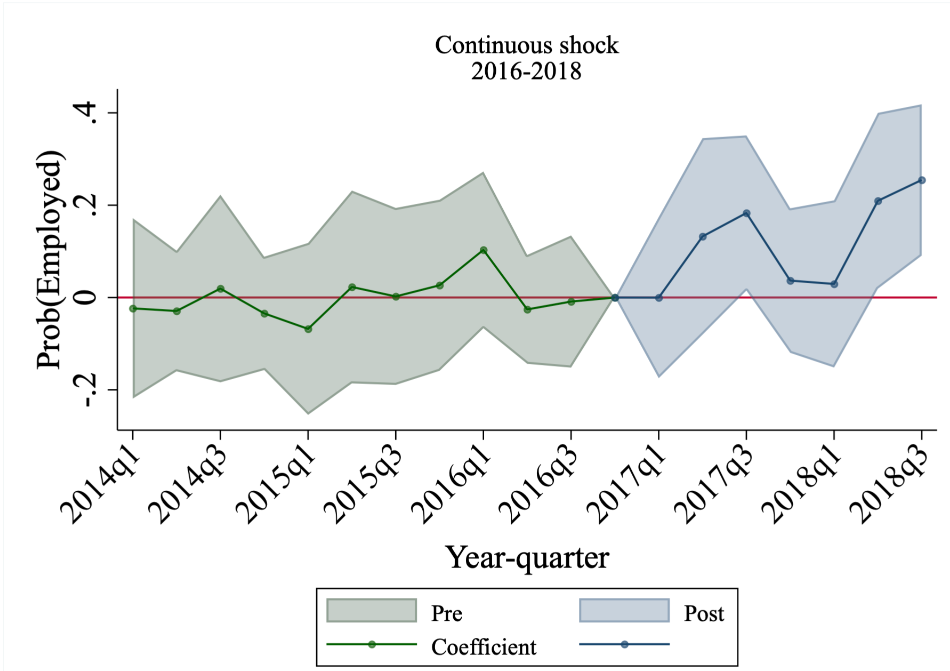

Note: This figure shows the means of transportation from Venezuela to Peru for the working-age Venezuelan sample in the Venezuelan Survey (ENPOVE). The working-age sample includes respondents between 15 and 65 years old that live in Lima and Callao. N=4,678

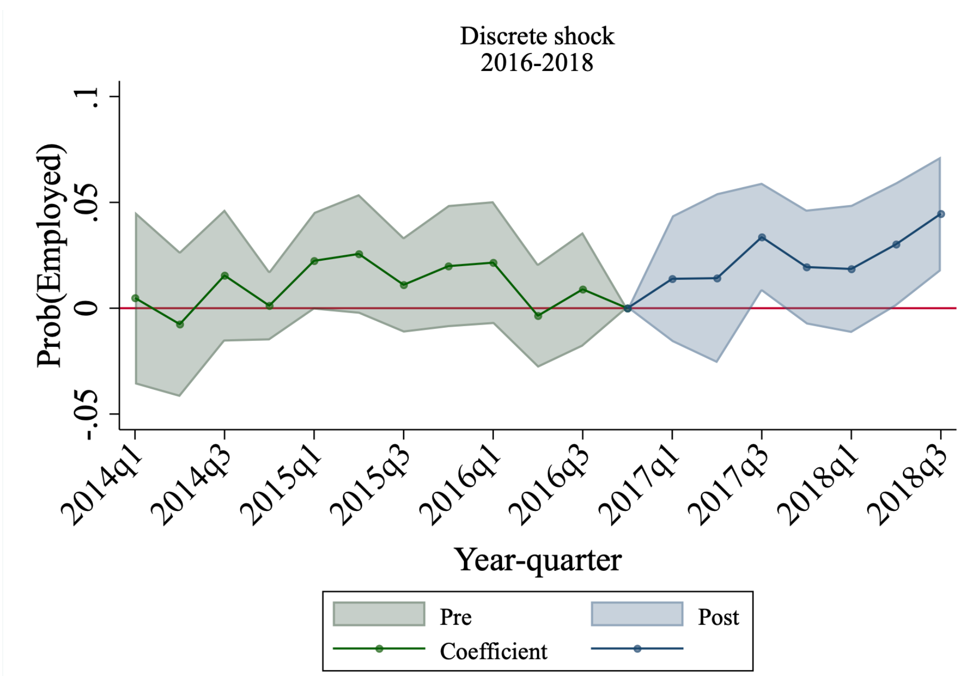
**Figure 4. Venezuelan immigrant characteristics**




Note: These figures show the age distribution, the skills, and sectors distribution of Venezuelan immigrants in 2018. The bottom panels (a) and (b) uses the sample of 4,678 Venezuelans between 15 and 65 years old in Lima and Callao from the Venezuelan Survey (ENPOVE). From this survey, I use the response whether they have any type of legal contract to identify those in the informal sector. Also, I define low-Skilled as those with a High-School diploma or less, and High-Skilled as those with more educational attainment than high-school.

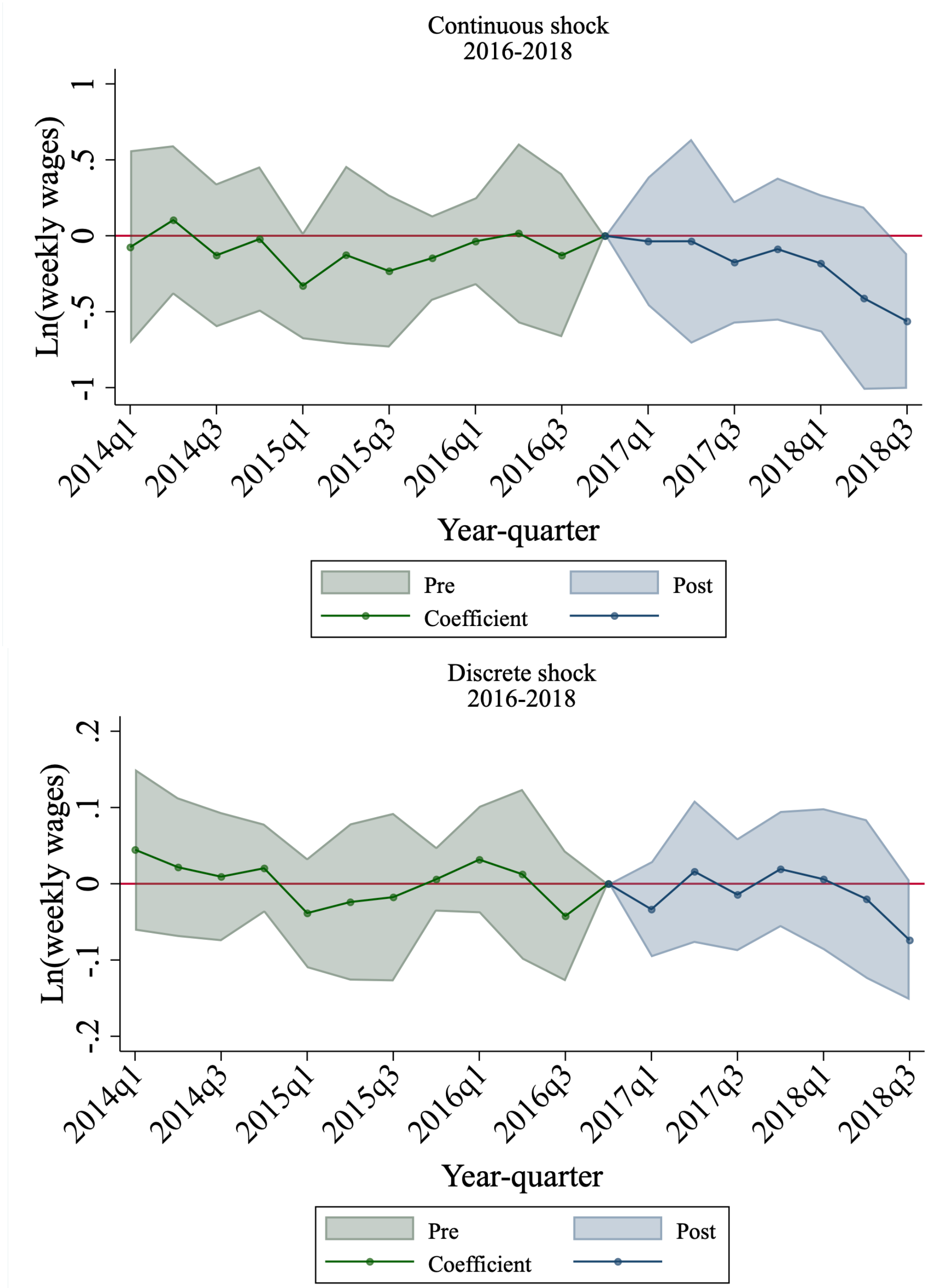
**Figure 5. Effect Of The Venezuelan-Born Influx On The Peruvian-Born Employment**




Note: The unit of observations are the Peruvian individuals between 15 and 65 years old from the Peruvian Labor Force Survey. Individual controls $Z'_{idt}$ include age, age squared, and male dummy. I calculate the standard errors clustered at the district level (42 districts)—confidence interval at 5% of significance.

**Figure 6. Effect Of The Venezuelan-Born Influx On The Peruvian-Born Weekly Wages**




Note: The unit of observations are the Peruvian individuals between 15 and 65 years old from the Peruvian Labor Force Survey. Individual controls $Z'_{idt}$ include age, age squared, and male dummy. I calculate the standard errors clustered at the district level (42 districts)—confidence interval at 5% of significance.

## Tables

**Table 1. Mean differences of the Peruvian working-age population before and after the immigration influx started in 2017**

| | (1) Before 2017 | (2) After 2017 | (3) Difference (1)-(2) | (4) p-value |
|---|---|---|---|---|
| ***Peruvian individual controls*** | | | | |
| Age | 36.79 | 37.09 | -0.30*** | 0.00 |
| Male | 0.47 | 0.47 | -0.00 | 0.15 |
| Years working for current employer | 1.62 | 2.04 | -0.42*** | 0.00 |
| Low-skill labor | 0.62 | 0.62 | -0.00 | 0.25 |
| Informal sector | 0.56 | 0.56 | -0.00 | 0.09 |
| ***Household characteristics*** | | | | |
| Household size | 10.75 | 12.65 | -1.90*** | 0.00 |
| Number of children | 2.94 | 3.46 | -0.52*** | 0.00 |
| ***Labor market outcomes*** | | | | |
| Prob(Employed) | 0.73 | 0.74 | -0.00 | 0.05 |
| Ln(weekly wages) | 4.54 | 4.57 | -0.03*** | 0.00 |
| Observations | 104,560 | 70,015 | | |

Note: This table shows the mean difference of Peruvian working-age individual characteristics before and after the large influx of Venezuelan immigrants started in 2017, so the unit of observation is the individual level.
***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

**Table 2. Mean difference between low- and high-immigrant neighborhoods of Lima and Callao in 2017 pre-Venezuelan exposure**

| | (1) High-Immigrant neighborhoods | (2) Low-Immigrant neighborhoods | (3) Difference (1)-(2) | (4) p-value |
|---|---|---|---|---|
| ***Labor market outcomes*** | | | | |
| Employment rate | 0.74 | 0.73 | 0.01*** | 0.00 |
| Ln weekly wages | 4.43 | 4.60 | -0.16*** | 0.00 |
| ***Firm characteristics*** | | | | |
| Number of formal firms (stock) | 3558 | 6195 | -2637*** | 0.00 |
| Share of firms | 0.01 | 0.02 | -0.01*** | 0.00 |
| Number of employees | 7.12 | 7.54 | -0.42*** | 0.00 |
| ***District Characteristics*** | | | | |
| Poverty rate, 2009 (%) | 20.13 | 13.90 | 6.23*** | 0.00 |
| Illiterate rate, 2007 (%) | 2.02 | 1.60 | 0.42*** | 0.00 |
| HH without water, Census 2007 (%) | 19.07 | 9.02 | 10.06*** | 0.00 |
| HH without sewer, Census 2007 (%) | 17.57 | 6.97 | 10.59*** | 0.00 |
| HH without street lighting, Census 2007 (%) | 7.58 | 2.86 | 4.71*** | 0.00 |
| ***Peruvian individual characteristics*** | | | | |
| Age | 35.93 | 37.03 | -1.10*** | 0.00 |
| Male | 0.48 | 0.47 | 0.01** | 0.00 |
| Years working for current employer | 1.56 | 1.82 | -0.26*** | 0.00 |
| Low-Skill labor | 0.67 | 0.57 | 0.11*** | 0.00 |
| Informal sector | 0.60 | 0.58 | 0.02*** | 0.00 |
| ***Household characteristics*** | | | | |
| Household size | 9.71 | 9.26 | 0.44*** | 0.00 |
| Number of children | 2.84 | 2.39 | 0.45*** | 0.00 |
| Observations | 38,582 | 96,962 | | |

Note: This table shows the mean difference between low- and high-immigrant neighborhoods in 2018 using the Venezuelan survey (ENPOVE). I define a high-immigrant dummy that takes 1 when the change in the share of Venezuelans in a district is above the percentile 75 of the Venezuelan net inflow distribution between 2016 and 2016. In this table, I restricted the sample to the Peruvian working-age population before the 1st quarter of 2017, so the unit of observation is the individual level.
***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

**Table 3. Effect Of The Venezuelan-Born Influx On The Peruvian-Born Labor Market Outcomes**

| | (1) Naïve OLS | (2) DID | (3) DID |
|---|---|---|---|
| ***Panel A. Dep. Variable: Prob(Employed)*** | | | |
| Share of Venezuelans | -0.0001 | | |
| | (0.0004) | | |
| Continuous $shock_d \times post_t$ | | 0.12*** | |
| | | (0.04) | |
| Discrete $shock_d \times post_t$ | | | 0.02** |
| | | | (0.01) |
| Time fixed effects | Yes | Yes | Yes |
| Districts fixed effects | Yes | Yes | Yes |
| Individual control variables | Yes | Yes | Yes |
| Observations | 350, 696 | 350, 696 | 350,696 |
| R-squared | 0.21 | 0.21 | 0.2 |
| Mean of dependent variable | 0.735 | 0.735 | 0.735 |
| ***Panel B. Dep. Variable: Ln(weekly wages)*** | | | |
| Share of Venezuelans | 0.006*** | | |
| | (0.0016) | | |
| Continuous $shock_d \times post_t$ | | -0.20*** | |
| | | (0.07) | |
| Discrete $shock_d \times post_t$ | | | -0.02*** |
| | | | (0.02) |
| Time fixed effects | Yes | Yes | Yes |
| Districts fixed effects | Yes | Yes | Yes |
| Individual control variables | Yes | Yes | Yes |
| Observations | 145,208 | 145,208 | 145,208 |
| R-squared | 0.23 | 0.15 | 0.15 |
| Mean of weekly wages (in 2018 US$) | 229.8 | 229.8 | 229.8 |

Note: This table shows the estimates of the naïve and difference-in-difference (DID) of the Venezuelan net inflow on the Peruvian-born labor market outcomes. The unit of observation for all the estimations are the individuals between 15 and 65 years old from the Peruvian Labor Force survey. Individual controls variable $Z'_{idt}$ include age, age squared, and male dummy. Clustered standard errors at the district level. 42 district.
***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

**Table 4. Effect Of The Venezuelan-Born Influx On The Peruvian-Born Labor Market Outcomes By Informal And Informal Sector**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | **Informal** | | | **Formal** | |
| | Naïve OLS | DID | DID | Naïve OLS | DID | DID |
| ***Panel A. Dep. Variable: Prob(Employed)*** | | | | | | |
| Share of Venezuelans | 0.0021*** | | | -0.0010 | | |
| | (0.0005) | | | (0.0007) | | |
| Continuous $shock_d \times post_t$ | | 0.06 | | | 0.12* | |
| | | (0.04) | | | (0.07) | |
| Discrete $shock_d \times post_t$ | | | 0.003 | | | 0.02* |
| | | | (0.006) | | | (0.01) |
| Observations | 182,943 | 181,877 | 182,900 | 130,459 | 129,769 | 130,382 |
| R-squared | 0.16 | 0.16 | 0.16 | 0.3057 | 0.31 | 0.31 |
| Mean of dependent variable | 0.820 | 0.820 | 0.820 | 0.613 | 0.613 | 0.613 |
| ***Panel B. Dep. Variable: Ln(weekly wages)*** | | | | | | |
| Share of Venezuelans | 0.0097*** | | | 0.0021 | | |
| | (0.0022) | | | (0.0013) | | |
| Continuous $shock_d \times post_t$ | | -0.02 | | | -0.19* | |
| | | (0.11) | | | (0.10) | |
| Discrete $shock_d \times post_t$ | | | -0.005 | | | -0.02 |
| | | | (0.02) | | | (0.02) |
| Observations | 58,030 | 57,672 | 58,013 | 72,069 | 71,717 | 72,030 |
| R-squared | 0.1792 | 0.18 | 0.18 | 0.2431 | 0.24 | 0.24 |
| Mean of weekly wages (in 2018 US$) | 4.121 | 4.122 | 4.121 | 4.833 | 4.833 | 4.832 |

Note: The unit of observation for all the estimations are the individuals between 15 and 65 years old from the Peruvian Labor Force survey. Individual controls $Z\_idt^{\wedge\prime}$ include age, age squared, and male dummy. All the estimations include districts and time fixed effects. Clustered standard errors at the district level. 42 district.
***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

**Table 5. Effect of The Venezuelan-Born Influx on Peruvian-Born Employment by skills within sectors**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | **Informal** | | | **Formal** | |
| Dep. Variable: Prob(Employed) | Naïve OLS | DID | DID | Naïve OLS | DID | DID |
| ***Panel A. Low-skilled sample*** | | | | | | |
| Share of Venezuelans | 0.0024*** | | | -0.0018** | | |
| | (0.0006) | | | (0.0009) | | |
| Continuous $shock_d \times post_t$ | | 0.02 | | | 0.10 | |
| | | (0.03) | | | (0.08) | |
| Discrete $shock_d \times post_t$ | | | 0.005 | | | 0.003 |
| | | | (0.01) | | | (0.01) |
| Observations | 127,714 | 126,960 | 127,700 | 68,552 | 68,158 | 68,533 |
| R-squared | 0.17 | 0.17 | 0.17 | 0.3465 | 0.35 | 0.35 |
| Mean of dependent variable | 0.815 | 0.815 | 0.815 | 0.440 | 0.439 | 0.440 |
| ***Panel B. High-skilled samples*** | | | | | | |
| Share of Venezuelans | 0.0016** | | | 0.0001 | | |
| | (0.0007) | | | (0.0009) | | |
| Continuous $shock_d \times post_t$ | | 0.16** | | | 0.15 | |
| | | (0.07) | | | (0.11) | |
| Discrete $shock_d \times post_t$ | | | 0.01 | | | 0.02* |
| | | | (0.01) | | | (0.01) |
| Observations | 55,229 | 54,917 | 55,200 | 61,907 | 61,611 | 61,849 |
| R-squared | 0.1427 | 0.14 | 0.14 | 0.1448 | 0.14 | 0.14 |
| Mean of dependent variable | 0.832 | 0.832 | 0.832 | 0.805 | 0.805 | 0.805 |

Note: The unit of observation for all the estimations are the individuals between 15 and 65 years old from the Peruvian Labor Force survey. Individual controls $Z\_idt^{\wedge\prime}$ include age, age squared, and male dummy. Clustered standard errors at the district level. 42 district. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

**Table 6. Effect of The Venezuelan-Born Influx on Peruvian-Born weekly wage by skills within sectors**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | **Informal** | | | **Formal** | |
| Dep. Variable: Ln(weekly wages) | Naïve OLS | DID | DID | Naïve OLS | DID | DID |
| ***Panel A. Low-skilled sample*** | | | | | | |
| Share of Venezuelans | 0.0104*** | | | 0.0019 | | |
| | (0.0020) | | | (0.0013) | | |
| Continuous $shock_d \times post_t$ | | 0.02 | | | -0.35** | |
| | | (0.15) | | | (0.13) | |
| Discrete $shock_d \times post_t$ | | | -0.003 | | | -0.05* |
| | | | (0.02) | | | (0.02) |
| Observations | 41,165 | 40,906 | 41,156 | 26,145 | 25,988 | 26,141 |
| R-squared | 0.2036 | 0.20 | 0.21 | 0.1723 | 0.17 | 0.17 |
| Mean of dependent variable | 57 | 57 | 57 | 92 | 92 | 92 |
| ***Panel B. High-skilled samples*** | | | | | | |
| Share of Venezuelans | 0.0062* | | | 0.0031** | | |
| | (0.0031) | | | (0.0015) | | |
| Continuous $shock_d \times post_t$ | | -0.24 | | | -0.12 | |
| | | (0.23) | | | (0.13) | |
| Discrete $shock_d \times post_t$ | | | -0.01 | | | -0.02 |
| | | | (0.04) | | | (0.02) |
| Observations | 16,865 | 16,766 | 16,857 | 45,924 | 45,729 | 45,889 |
| R-squared | 0.1458 | 0.15 | 0.15 | 0.2464 | 0.25 | 0.25 |
| Mean of weekly wages (in 2018 US$) | 74.66 | 74.66 | 74.66 | 150 | 150 | 150 |

Note: The unit of observation for all the estimations are the individuals between 15 and 65 years old from the Peruvian Labor Force survey. Individual controls $Z\_idt^{\wedge\prime}$ include age, age squared, and male dummy. Clustered standard errors at the district level. 42 district. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

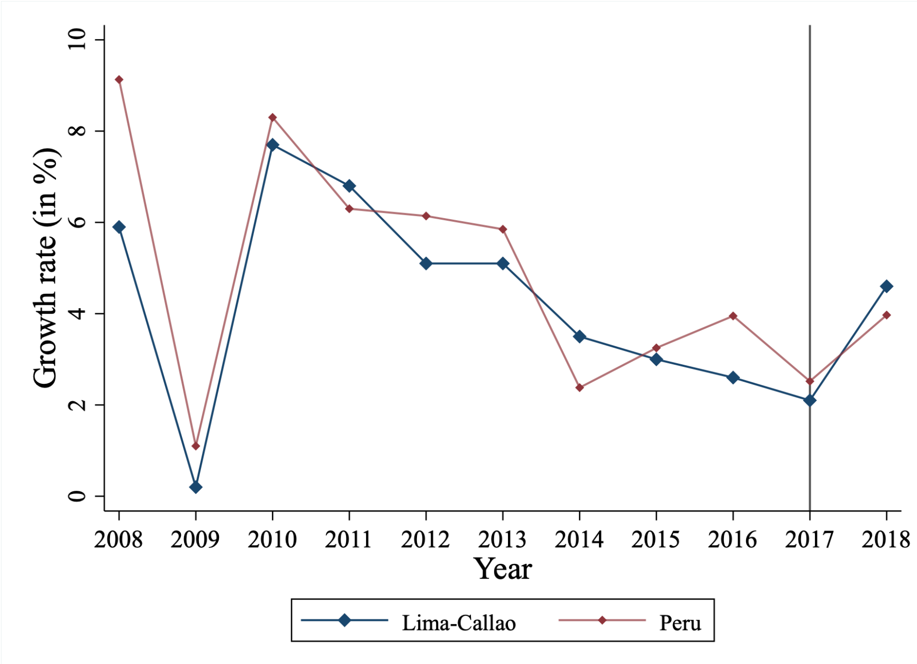
# Appendix

## A. Figures

**Figure A. 1. Venezuelan immigrants by country in Latin America and the Caribbean region**

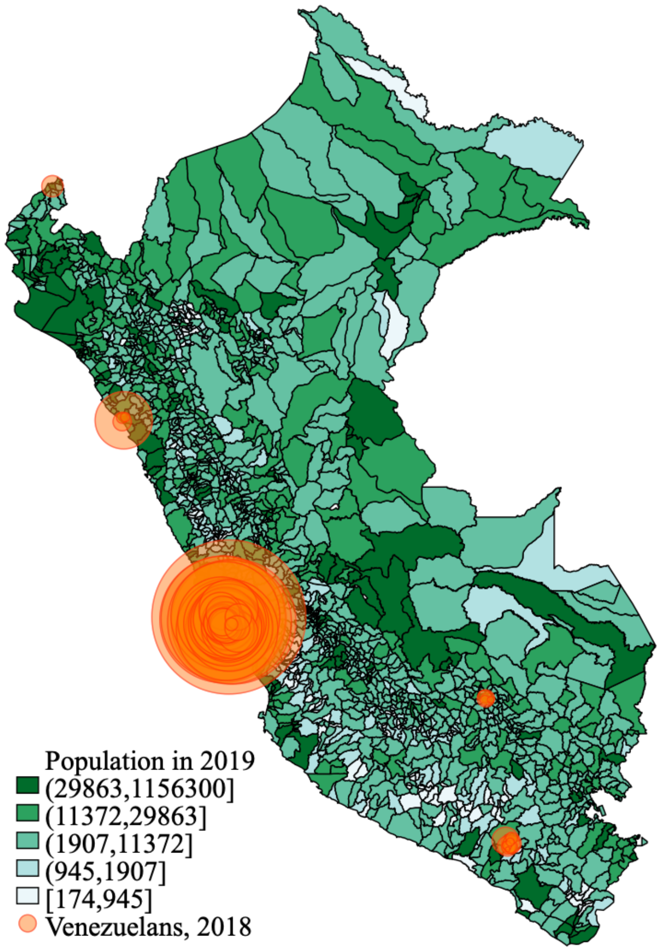

Source: Inter-Agency Coordination Platform for Refugees and Migrants from Venezuela (downloaded from https://www.r4v.info on September 2022)

**Figure A. 2. Economic growth rate in Lima-Callao and Peru**



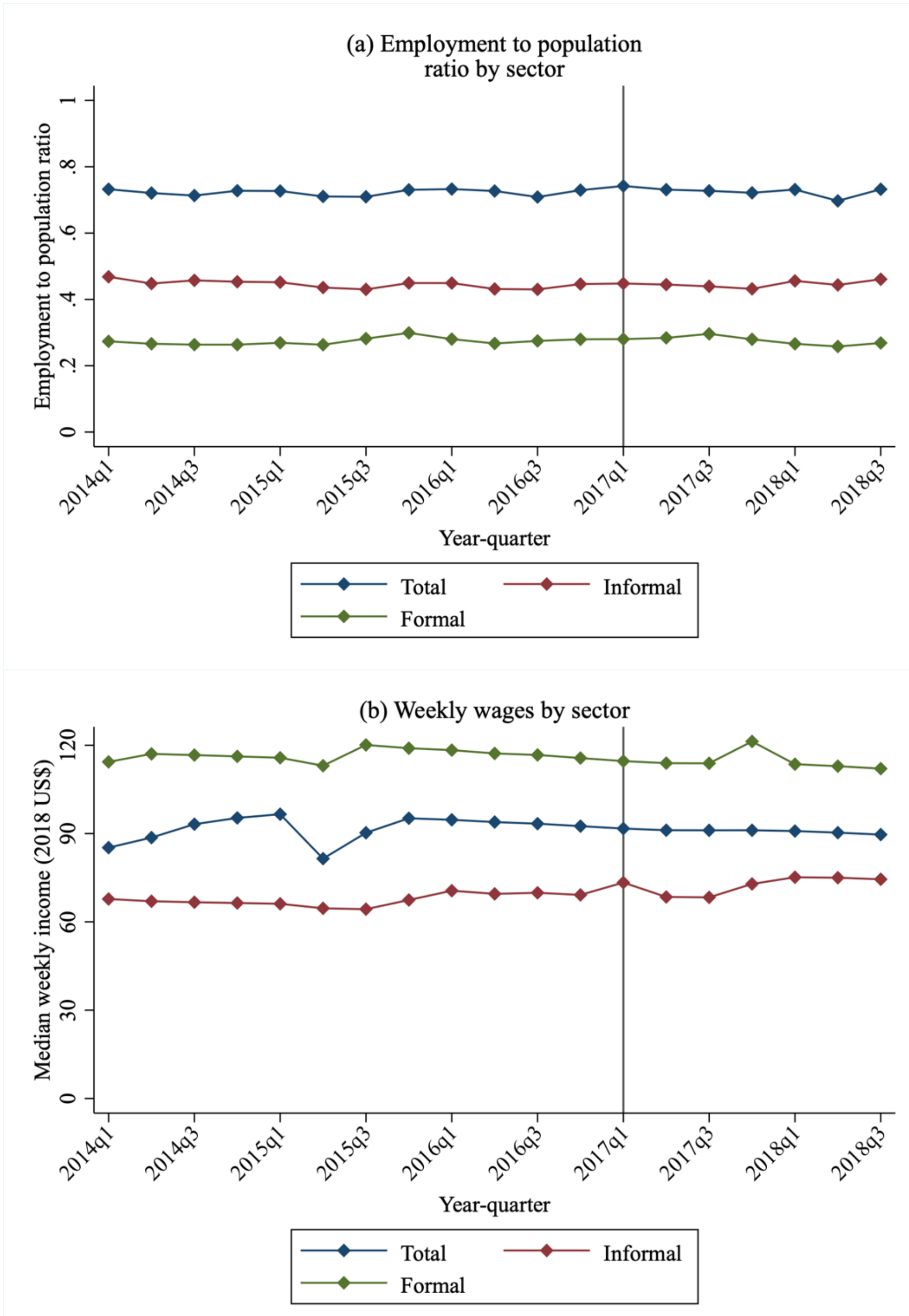

Source: Instituto Pervuano de Economia (IPE)

**Figure A. 3. Peruvian and Venezuelan geographic distribution, 2018 and 2019**



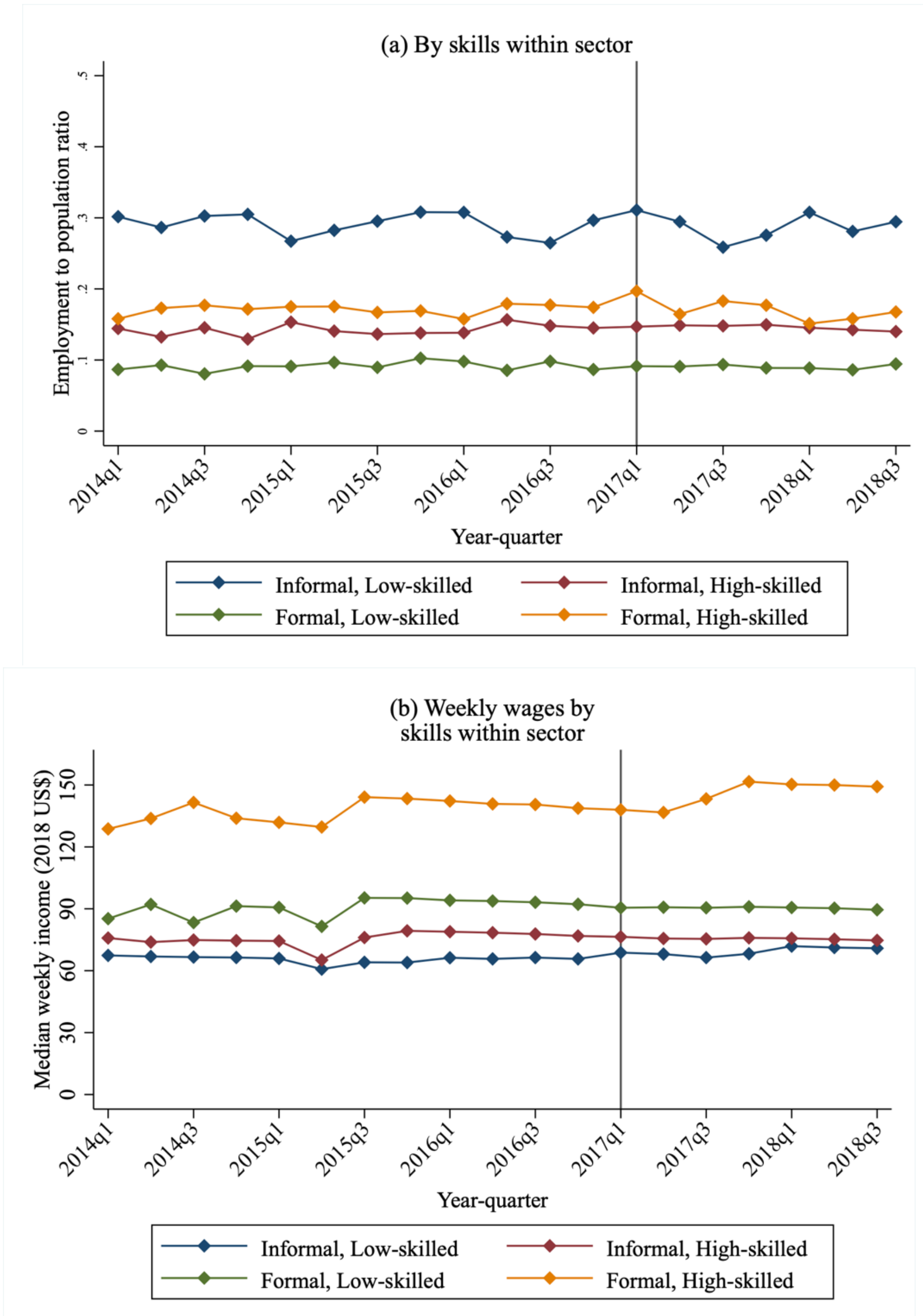

Note: This map shows the distribution of the Peruvian and Venezuelan populations in 2019. Sources: latest INEI update on the Peruvian population estimates in 2019, and the Venezuelan Survey (ENPOVE) in 2018 for the Venezuelan population. The circles' sizes are proportional to the number of Venezuelans.

**Figure A. 4. Raw trends of Peruvian-born labor market outcomes by sector in Lima and Callao, 2014-2018**



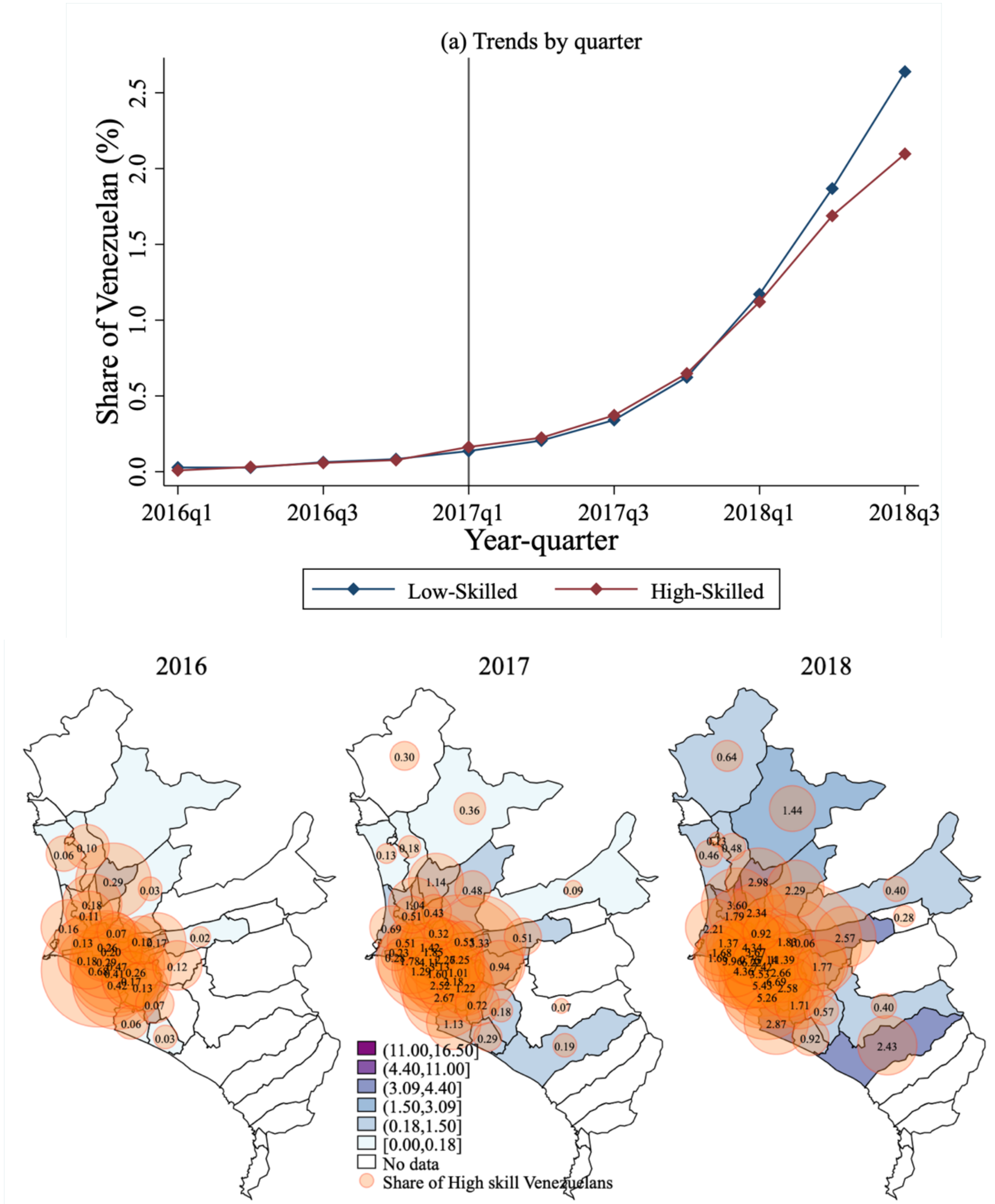

Note: This figure shows the median employment to population ratio and weekly income across neighborhoods in Lima and Callao between 2014 and 2018 for overall Peruvians and by formal and informal sectors. I define the informal sector as individuals that belong to either category: (i) without health insurance, (ii) working in a small firm size with 10 or fewer employees, or (iii) Self-employed. Panel (a) show the raw median employment to population ratio pooled and by sector, and (b) the raw median weekly income in 2018 US$ by sector. The vertical gray line indicates the moment of introduction of the working permit in January 2017 and the start of the migration phenomenon increase.

**Figure A. 5. Raw trends of Peruvian-born labor market outcomes by skills within sector in Lima and Callao, 2014-2018**



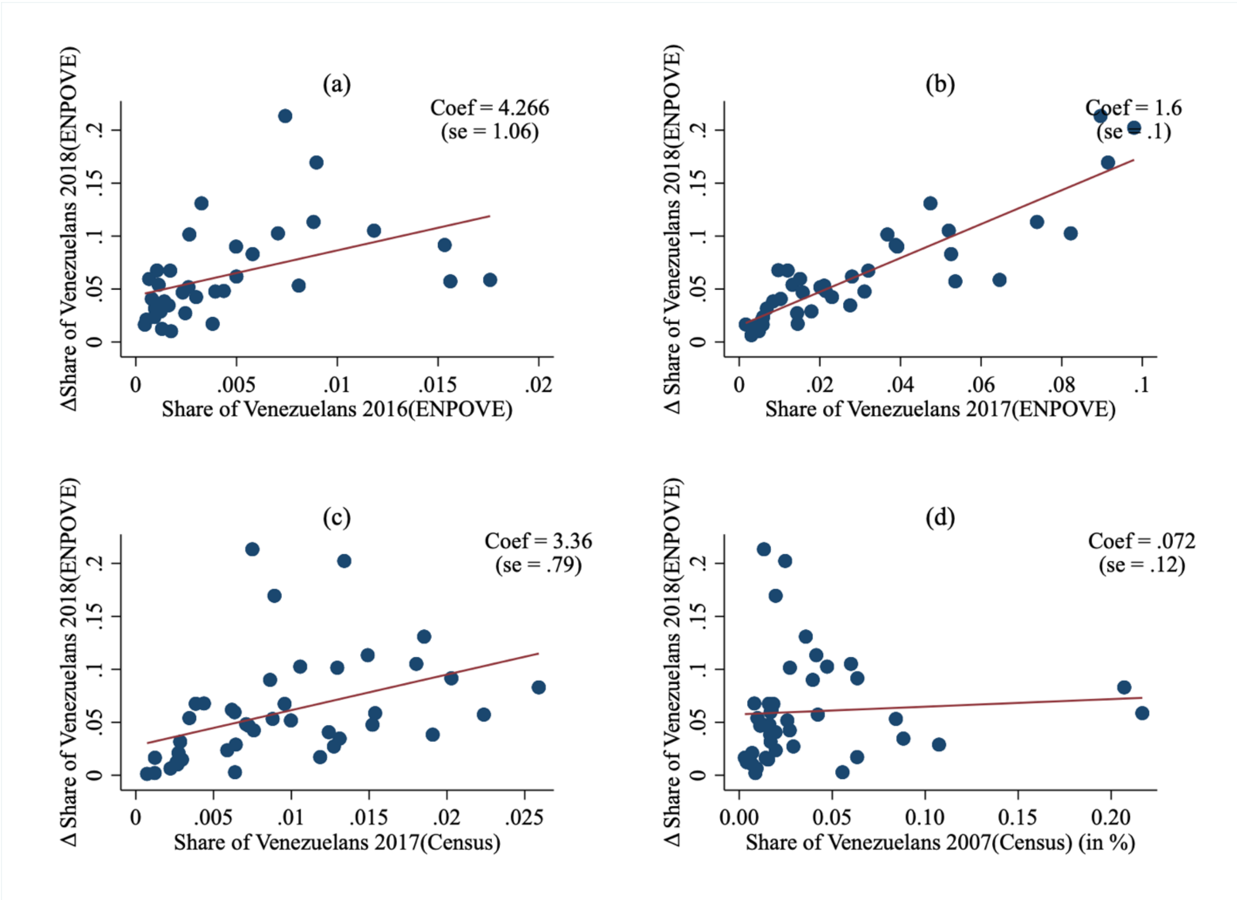

Note: This figure shows the median employment to population ratio and weekly income across neighborhoods in Lima and Callao between 2014 and 2018 for overall Peruvians and by formal and informal sectors. I define the informal sector as individuals that belong to either category: (i) without health insurance, (ii) working in a small firm size with 10 or fewer employees, or (iii) Self-employed. Also, I define low-skilled as those with a high-school diploma or less and high-skilled as those with more educational attainment than high school. Panel (a) show the raw median employment to population ratio pooled and by sector, and (b) the raw median weekly income in 2018 US$ by sector. The vertical gray line indicates the moment of introduction of the working permit in January 2017 and the start of the migration phenomenon increase.

**Figure A. 6. Time variation and spatial variation of the share of Venezuelan immigrants (in %) by skills, 2016-2018**



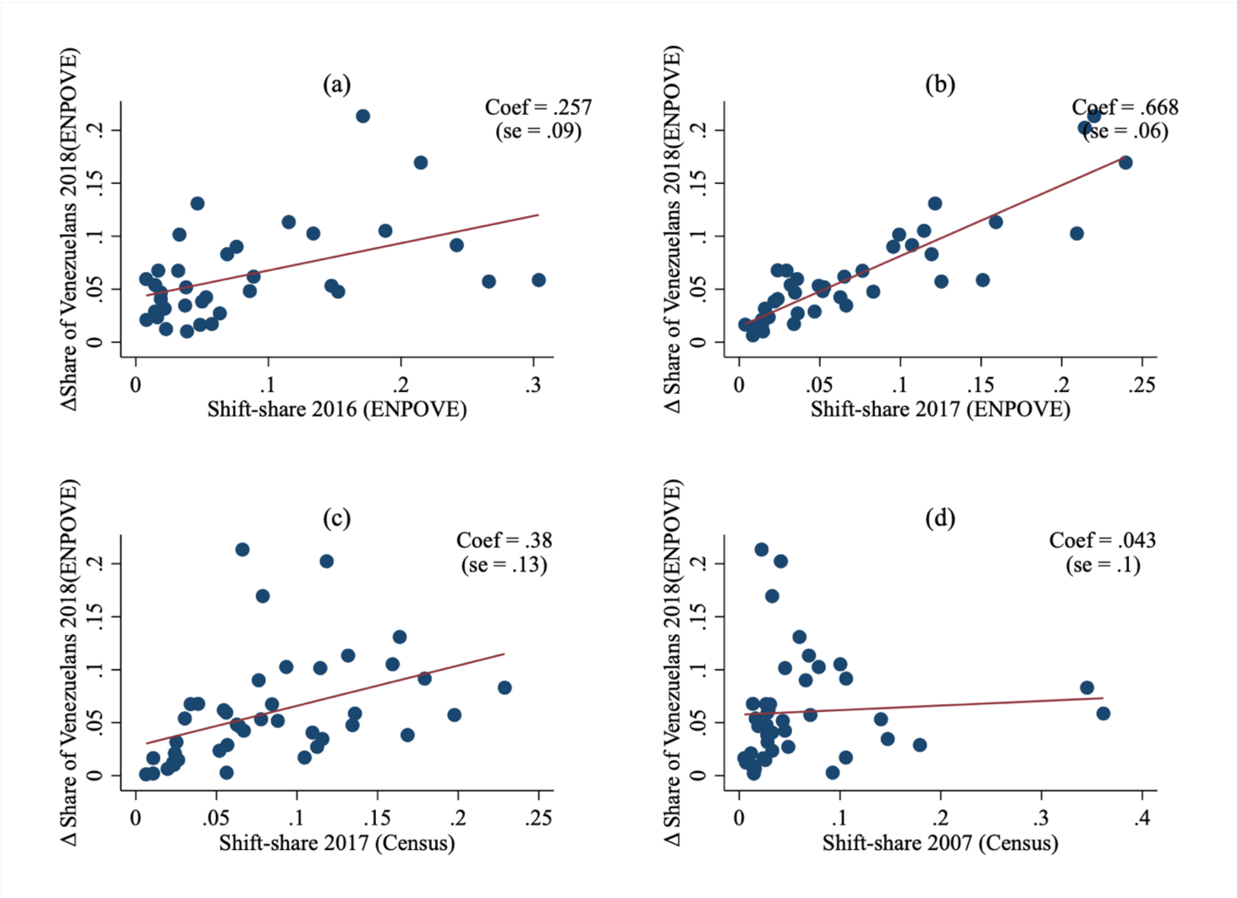

Note: These figures show the time and geographic distribution of the low- and high-skill share of Venezuelans in Lima and Callao districts between 2016 and 2018. This share of Venezuelans by skilled is measure from the Venezuelan survey (ENPOVE) relative to the working age population in Lima and Callao from the Peruvian Labor Force Survey (LFS). I define low-Skilled as those with a High-School diploma or less, and High-Skilled as those with more educational attainment than high school. The upper panel shows the cumulative share of Venezuelans the population between 14 and 65 years old in January 2017 (in %) from the Venezuelan survey (ENPOVE) by broad skill group. In the bottom panel, the scale of purple indicates the low-skill share. The orange circles are proportional to the high-skill share of Venezuelans with the corresponding number. The vertical gray line indicates the introduction of the working permit in January 2017, which is a legal immigrant status for Venezuelans.

**Figure A. 7.Partial correlations between the net inflow of Venezuelans in 2018 and the share of Venezuelan immigrants in 2016 and 2017 from different data sources**




Note: This figure shows the partial correlation between the net influx of Venezuelans in 2018 and the share in previous years using different data sources. Panel (a) and (b) use the share of Venezuelan calculated using the Venezuelan Survey ENPOVE and the Peruvian LFS in 2016 and 2017, respectively. Panel (c) and (d) use the Census in 2017 and 2007, respectively. The red line represents the linear projection from the OLS estimation.

**Figure A. 8. Partial correlations between the net inflow of Venezuelans in 2018 and two shift-share definitions from different data sources**




Note: This figure shows the partial correlation between the net influx of Venezuelans in 2018 and different definitions of the shift-share instrument using two data sources (see subsection 7.2.2). Panel (a) and (d) use the shift-share in equation (6) measured using the Venezuelan Survey ENPOVE and the Peruvian LFS in 2016 and 2017, respectively. Panel (c) and (d) use the shift-share in equation (7) from Census in 2017 and 2007, respectively. The red line represents the linear projection from the OLS estimation.

## B. Tables

**Table B. 1. Descriptive statistics of immigrants travel time between Venezuela and Peru**

| stats | Travel time (in months) |
|---|---|
| mean | 0.55 |
| sd | 2.5 |
| | |
| min | 0 |
| p5 | 0 |
| p25 | 0 |
| p50 | 0 |
| p75 | 0 |
| p95 | 2 |
| max | 71 |
| N | 7,859 |

Note: This table shows the descriptive statistics of the travel time (in months) of immigrants between Venezuela and Peru for the working-age Venezuelan sample in the Venezuelan Survey (ENPOVE). The working-age sample includes respondents between 15 and 65 years old.

**Table B. 2. Observations of Venezuelans' location by skilled group from the Venezuelan Survey (ENPOVE)**

| Grouped neighborhoods | High-skilled | Low-skilled | Total |
|---|---|---|---|
| Lima North | 300 | 479 | 779 |
| Lima East | 336 | 386 | 722 |
| Lima Center | 296 | 322 | 618 |
| Lima South | 269 | 406 | 675 |
| Callao | 282 | 407 | 689 |
| Total | 1,483 | 2,000 | 3,483 |

Note: Number of observations of Venezuelans by area within Lima and Callao from the analytical sample using the Venezuelan Survey (ENPOVE)

**Table B. 3. Comparison of Venezuelan characteristics over time**

| Variable | N | (1) 2016 Mean/SE | N | (2) 2017 Mean/SE | N | (3) 2018 Mean/SE | t-test Difference (1)-(2) | t-test Difference (1)-(3) | t-test Difference (2)-(3) | F-test for joint orthogonality |
|---|---|---|---|---|---|---|---|---|---|---|
| Male | 204 | 0.510 | 988 | 0.549 | 3534 | 0.517 | -0.039 | -0.007 | 0.032* | 0.197 |
| | | [0.035] | | [0.016] | | [0.008] | | | | |
| Age | 204 | 36.471 | 988 | 32.504 | 3294 | 31.323 | 3.967*** | 5.147*** | 1.181*** | 0.000*** |
| | | [0.933] | | [0.344] | | [0.179] | | | | |
| Cohabiting or Married | 204 | 0.667 | 988 | 0.620 | 3534 | 0.525 | 0.046 | 0.142*** | 0.096*** | 0.000*** |
| | | [0.033] | | [0.015] | | [0.008] | | | | |
| Widow(er) | 204 | 0.010 | 988 | 0.006 | 3534 | 0.008 | 0.004 | 0.002 | -0.002 | 0.809 |
| | | [0.007] | | [0.002] | | [0.001] | | | | |
| Divorced | 204 | 0.015 | 988 | 0.007 | 3534 | 0.009 | 0.008 | 0.006 | -0.002 | 0.560 |
| | | [0.008] | | [0.003] | | [0.002] | | | | |
| Separated | 204 | 0.039 | 988 | 0.024 | 3534 | 0.024 | 0.015 | 0.015 | -0.000 | 0.411 |
| | | [0.014] | | [0.005] | | [0.003] | | | | |
| Single | 204 | 0.270 | 988 | 0.342 | 3534 | 0.407 | -0.072** | -0.138*** | -0.065*** | 0.000*** |
| | | [0.031] | | [0.015] | | [0.008] | | | | |
| Without education | 154 | 0.000 | 721 | 0.001 | 2490 | 0.000 | -0.001 | -0.000 | 0.001 | 0.604 |
| | | [0.000] | | [0.001] | | [0.000] | | | | |
| Pre-scholar | 154 | 0.000 | 721 | 0.000 | 2490 | 0.000 | N/A | -0.000 | -0.000 | 0.839 |
| | | [0.000] | | [0.000] | | [0.000] | | | | |
| Incomplete Primary Education | 154 | 0.045 | 721 | 0.022 | 2490 | 0.040 | 0.023 | 0.005 | -0.018** | 0.064* |
| | | [0.017] | | [0.005] | | [0.004] | | | | |
| Complete Primary Education | 154 | 0.084 | 721 | 0.085 | 2490 | 0.118 | -0.000 | -0.034 | -0.033** | 0.024** |
| | | [0.022] | | [0.010] | | [0.006] | | | | |
| Incomplete High School | 154 | 0.071 | 721 | 0.055 | 2490 | 0.097 | 0.016 | -0.025 | -0.041*** | 0.002*** |
| | | [0.021] | | [0.009] | | [0.006] | | | | |
| Complete High School | 154 | 0.305 | 721 | 0.355 | 2490 | 0.345 | -0.050 | -0.040 | 0.010 | 0.497 |
| | | [0.037] | | [0.018] | | [0.010] | | | | |
| Some college | 154 | 0.071 | 721 | 0.062 | 2490 | 0.043 | 0.009 | 0.028* | 0.019** | 0.040** |
| | | [0.021] | | [0.009] | | [0.004] | | | | |

**Table B.1. continues**

| Variable | (1) 2016 N | (1) 2016 Mean/SE | (2) 2017 N | (2) 2017 Mean/SE | (3) 2018 N | (3) 2018 Mean/SE | t-test Difference (1)-(2) | t-test Difference (1)-(3) | t-test Difference (2)-(3) | F-test for joint orthogonality |
|---|---|---|---|---|---|---|---|---|---|---|
| Graduate Collage | 154 | 0.273 | 721 | 0.240 | 2490 | 0.198 | 0.033 | 0.075** | 0.042** | 0.007*** |
| | | [0.036] | | [0.016] | | [0.008] | | | | |
| Incomplete University | 154 | 0.149 | 721 | 0.179 | 2490 | 0.158 | -0.030 | -0.009 | 0.021 | 0.376 |
| | | [0.029] | | [0.014] | | [0.007] | | | | |
| TPP applicants | 204 | 0.255 | 988 | 0.788 | 3534 | 0.851 | -0.534*** | -0.596*** | -0.062*** | 0.000*** |
| | | [0.031] | | [0.013] | | [0.006] | | | | |
| At least one HH member apply for the TPP | 204 | 0.255 | 988 | 0.788 | 3534 | 0.851 | -0.534*** | -0.596*** | -0.062*** | 0.000*** |
| | | [0.031] | | [0.013] | | [0.006] | | | | |
| Household size | 204 | 3.456 | 988 | 3.349 | 3534 | 3.368 | 0.107 | 0.088 | -0.019 | 0.773 |
| | | [0.116] | | [0.058] | | [0.033] | | | | |
| Number of children | 204 | 0.608 | 988 | 0.591 | 3534 | 0.570 | 0.017 | 0.038 | 0.021 | 0.690 |
| | | [0.058] | | [0.026] | | [0.015] | | | | |
| =1 if sons between 17 and 12 years old | 204 | 0.201 | 988 | 0.127 | 3534 | 0.124 | 0.074** | 0.077*** | 0.003 | 0.015** |
| | | [0.032] | | [0.011] | | [0.006] | | | | |
| =1 if sons between 12 and 6 years old | 204 | 0.270 | 988 | 0.219 | 3534 | 0.200 | 0.051 | 0.070** | 0.019 | 0.096* |
| | | [0.035] | | [0.015] | | [0.008] | | | | |
| =1 if sons under 6 years old | 204 | 0.137 | 988 | 0.242 | 3534 | 0.244 | -0.105*** | -0.106*** | -0.002 | 0.013** |
| | | [0.026] | | [0.015] | | [0.009] | | | | |

The value displayed for t-tests is the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

**Table B. 4. First-Stage Regression of the net Venezuelan Immigration using the past settlement instrument**

| VARIABLES | (1)<br>Δ Share of Venezuelans 2018 | (2)<br>Δ Share of Venezuelans 2018 | (3)<br>Δ Share of Venezuelans 2018 | (4)<br>Δ Share of Venezuelans 2018 |
|---|---|---|---|---|
| Share of Venezuelans, 2016 (ENPOVE) | 6.491** | | | |
| | (2.699) | | | |
| Share of Venezuelans, 2017 (ENPOVE) | | 1.679*** | | |
| | | (0.189) | | |
| Share of Venezuelans (Census 2017) | | | 3.402*** | |
| | | | (0.958) | |
| Share of Venezuelans (Census 2007) | | | | 0.130 |
| | | | | (0.108) |
| Observations | 35 | 40 | 43 | 42 |
| R-squared | 0.264 | 0.786 | 0.168 | 0.010 |
| F-statistic | 5.782 | 79.20 | 12.62 | 1.450 |

Note: This table shows the estimates for the first stage equation **Error! Reference source not found.**. The dependent variable i s the change in the share of Venezuelans in 2018. Column (1) and column (2) use past shares calculated from the Venezuelan Survey ENPOVE and the Peruvian LFS. Columns (3) and (4) use past shares calculated from the Census in 2007 and 2017. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table B. 5. Two district in Lima as leading examples of the first-stage estimation problem**

| District | Share of Venezuelan 2017 | Share of Venezuelan 2007 | Share of Venezuelans 2016 | Share of Venezuelans 2017 | Share of Venezuelans 2018 | Δ share of Venezuelan 2018 |
|---|---|---|---|---|---|---|
| LIMA | 0.0086 | 0.0004 | 0.005 | 0.039 | 0.130 | 0.090 |
| SURQUILLO | 0.0185 | 0.0004 | 0.003 | 0.047 | 0.180 | 0.131 |
| Data source | Census | Census | ENPOVE | ENPOVE | ENPOVE | ENPOVE |

**Table B. 6. Percent of the Venezuelan sample by state of origin**

| **Venezuelan State name (in Spanish)** | **Percent of the Venezuelan Survey sample** |
|---|---|
| Distrito Capital | 13.86 |
| Estado Carabobo | 11.27 |
| Estado Lara | 10.28 |
| Estado Zulia | 7.35 |
| Estado Aragua | 7.33 |
| Estado Anzoategui | 6.37 |
| Estado Miranda | 5.52 |
| Estado Tachira | 4.92 |
| Estado Monagas | 3.97 |
| Estado Barinas | 3.91 |
| Estado Merida | 3.72 |
| Estado Portuguesa | 3.55 |
| Estado Bolivar | 2.98 |
| Estado Trujillo | 2.77 |
| Estado Falcon | 2.12 |
| Estado Yaracuy | 2.09 |
| Estado Nueva Esparta | 1.71 |
| Estado Vargas | 1.62 |
| Estado Sucre | 1.45 |
| Estado Cojedes | 1.18 |
| Estado Guarico | 1.15 |
| Estado Apure | 0.71 |
| Estado Delta Amacuro | 0.13 |
| Estado Amazonas | 0.04 |

Note: This table shows the percent of Venezuelan respondents between 15 and 65 years old by state of origin using the Venezuelan Survey (ENPOVE)

## C. Additional details on the Peruvian immigration policy for Venezuelan immigrants

The TPP requires some paperwork and a fee of $12 (Decreto Supremo N° 002-2017-IN, 2017).In particular, the filing includes an online application form, the passport or national ID photocopy, and evidence of non-criminal records (affidavit of not having a criminal and judicial record at the national and international level and International Exchange Card, INTERPOL). Finally, to be eligible, they need to enter the country and apply before specific deadlines.

Between 2017 and 2018, the Peruvian Government changed the entry date requirement and the application deadline in several opportunities (Decreto Supremo N° 002-2017-IN, 2017; Decreto Supremo Nº 023-2017-IN, 2017; Decreto Supremo Nº 001-2018-IN, 2018). It is not clear whether the changes of deadline for eligibility is a response of the Government to the large inflow of Venezuelan or of if those deadline changes increase the arrival of the immigrants in Peru. More importantly, the January 2018 reform extended the entry and application deadlines by one year and a half as Table C. 1 shows. In particular, the new migration law passed in March 2017 introduces the possibility to change from the TPP temporary document to permanent resident legal status. Thus, this work permit TPP was originally thought of only as a temporary instrument to help Venezuelan access legal and permanent status to work.

**Table C. 1. Regulation for Venezuelan immigrants in Peru**

| Month-Year | Policy change | Entry deadline | Application deadline | Change in the available time w.r.t. to the decree issue date | |
|---|---|---|---|---|---|
| | | | | To enter the country | To apply |
| Jan-2017 | TPP law introduction | Feb-17 | jun-17 | - | - |
| mar-17 | Migration Law | | | | |
| Jul-17 | 1st reform | Jul-17 | oct-17 | 1 month | 5 months |
| Jan-2018 | 2nd reform | Dec-18 | jun-19 | 12 months | 18 months |
| Aug-2018 | 3rd reform | Oct-18 | dec-18 | 3 months | 5 months |

Note: This table shows the migration policy changes in Peru, by the date the regulation pass, the eligibility deadline changes, and the additional time each reform gives to the Venezuelans to enter and apply for the work permit.

## a. Comparison of the working permit for Venezuelan workers to other immigrant regulations in the US and Colombia

Peru has several characteristics that make it especially different from Colombia to local policies and migration flows. First, the Peruvian Government introduces the special work permit for Venezuelans in January 2017, while the Colombian Government responds to the incoming migrant flow in September 2017 (Migracion Colombia, 2017; Decreto Supremo N° 002-2017-IN, 2017). Second, Colombia also experiences the Colombia-born return from Venezuela to Colombia (Caruso et al., 2019), while Peru does not count in that phenomenon. Third, the Peruvian Government's goal of the policy is a transitional policy to eventually give permanent residency to Venezuelans with the New Migration law in 2017 (Ley y Reglamento de Migraciones, 2017). Finally, Colombia closed its border to Venezuelans in December 2016 and August 2017 (Santamaria, 2020b; Torrado et al., 2019), while Peru does not share common borders with Venezuela. Therefore, the Peruvian scenario is particularly interesting to estimate the total effect of this short-term policy and migrant flows in the natives' labor outcomes.

Compared to other countries, Peru has a flexible regime for incorporating migrants into the labor force. For instance, the US does not count on a significant inflow of migrants with the Temporary Protected Status (TPS) such as the Venezuelans in Peru with the TPP. To illustrate the Venezuelan shock in Peru, while Peru issued the TPP permit for almost 81% of the Venezuelans, which are 16% of the Peruvian labor force, the US issued the TPS for almost 72% of the Salvadorans which are 0.21% of the US labor force in 2014 (Orrenius & Zavodny, 2015).Further, the TPP in Peru reaches a larger migrant population than the TPS for any migration group in the US. First, Venezuelan refugees are not included in the currently designated countries that offer the TPS . Second, the TPS requires more paperwork and costs 45 times the TPP fee in Peru . Therefore, with a migration policy that legalizes migrants, Peru received an unprecedented inflow of migrants from Venezuela different from any experience in the US.

## D. Limitations and comparison among data sources for the past share of Venezuelan immigrants measurement

One main limitation of the time-varying measure of the share of Venezuelans in equation (1) from the ENPOVE and LFS survey is that the sample has fewer district observations than the Census.

This is because the LFS has observations only from 40 districts, while the Census 2017 includes all 50 districts in Lima and Callao provinces. Table D.1. shows the number of districts with a share of Venezuelans by quarter between 2010 and 2018. As a result, the shares that are constructed with ENPOVE and the LFS are limited geographically with more missing values than the Census. For the main specifications, I focus on the period between 2016 and 2018 because at least more than 10 districts have a non-missing share of Venezuelans. Since there are several missing values mostly between 2011 and 2016, Table D.2. reports the estimates of a linear probability model of having a missing value of the share in each district. Overall, the district control variables I use in my main specifications are not correlated with the probability of missing values on the share of Venezuelans. Thus, the share of Venezuelans this correlation suggests that the share of Venezuelans is not correlated with economic conditions at the district level.

The share of Venezuelans relies on two underlying assumptions regarding variable construction. First, the percent of Venezuelans using arrivals assume that these immigrants stay as long as December 2018 when the ENPOVE survey was conducted. A plausible hypothesis is that Peru is a temporary host country and not the final destination. According to the ENPOVE survey, only 5.3% of the respondents in 2018 want to immigrate to Chile, Argentina, Brazil, and other countries. This decision of staying in Peru is also consistent considering the working permit for Venezuelans that allows them to work and aims to be a transitional immigrant status for a permanent residency in Peru. Thus, it is a reasonable assumption that most of the immigrants stay in Peru, and I am not missing a significant temporary shock.

Another possibility behind the share of Venezuelans' calculation is that many of the Venezuelans before 2018 migrated to another country, which I do not observe in the ENPOVE sample. In the Venezuelan survey sample, only 3% of the Venezuelan migrants arrived before 2016, and most of the respondents arrived after 2018. These percentages of arrival over time are consistent with the trends for Colombia and Peru previously documented (Caruso et al., 2019; Groeger et al., 2021; Santamaria, 2020) as well as the Regional Interagency Coordination Platform for Refugees and Migrants of Venezuela (UNHCR, 2022). Therefore, the share of Venezuelans using the arrivals date assume reasonably that most of the immigrants stay in Peru, and it can be considered as an upper bound measure of the immigrants that actively participate in the Peruvian labor market.

**Table D. 1. Number of districts with the share of Venezuelans**

| Year-quarter | Number of districts with the share of Venezuelans |
|---|---|
| 2010q1 | 0 |
| 2010q2 | 0 |
| 2010q3 | 0 |
| 2010q4 | 0 |
| 2011q1 | 1 |
| 2011q2 | 0 |
| 2011q3 | 0 |
| 2011q4 | 2 |
| 2012q1 | 0 |
| 2012q2 | 2 |
| 2012q3 | 1 |
| 2012q4 | 0 |
| 2013q1 | 2 |
| 2013q2 | 0 |
| 2013q3 | 0 |
| 2013q4 | 0 |
| 2014q1 | 1 |
| 2014q2 | 2 |
| 2014q3 | 1 |
| 2014q4 | 2 |
| 2015q1 | 4 |
| 2015q2 | 2 |
| 2015q3 | 5 |
| 2015q4 | 8 |
| 2016q1 | 12 |
| 2016q2 | 17 |
| 2016q3 | 23 |
| 2016q4 | 22 |
| 2017q1 | 29 |
| 2017q2 | 32 |
| 2017q3 | 37 |
| 2017q4 | 38 |
| 2018q1 | 41 |
| 2018q2 | 40 |
| 2018q3 | 42 |
| 2018q4 | 39 |

Note: This table shows the number of districts with information about the share of Venezuelan constructed using the Venezuelan survey and the Peruvian Labor Force Survey.

**Table D. 2. Linear probability model on the missing value of the share of Venezuelans**

| | (1)<br>Missing value |
|---|---|
| $\Delta \ln(labor\ force)$ | -0.02 |
| | (0.03) |
| Δ Number of firms | -0.00 |
| | (0.00) |
| D(2016q1=1) ×Poverty rate 2009 | 0.32 |
| | (0.93) |
| D(2016q2=1) ×Poverty rate 2009 | -0.59 |
| | (0.96) |
| D(2016q3=1) ×Poverty rate 2009 | -1.24 |
| | (0.93) |
| D(2016q4=1) ×Poverty rate 2009 | -0.04 |
| | (0.83) |
| D(2017q2=1) ×Poverty rate 2009 | 0.11 |
| | (0.86) |
| D(2017q3=1) ×Poverty rate 2009 | -0.35 |
| | (0.78) |
| D(2017q4=1) ×Poverty rate 2009 | -0.61 |
| | (0.80) |
| D(2018q1=1) ×Poverty rate 2009 | -0.85 |
| | (0.77) |
| D(2018q2=1) ×Poverty rate 2009 | -0.85 |
| | (0.78) |
| D(2018q3=1) ×Poverty rate 2009 | -1.16 |
| | (0.77) |
| D(2018q4=1) ×Poverty rate 2009 | -1.20* |
| | (0.71) |
| | |
| Observations | 696 |
| R-squared | 0.62 |
| Clustered at district level | Yes |

Note: This table shows the regression of a missing value of the share of Venezuelans on the district controls variables used in the main specification. The missing value dummy takes 1 when there is no share of Venezuelans on a district d time t. D(*t*=1) is the dummy variable that takes 1 for each moment. The baseline is 2017q1. Clustered standard errors by districts in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## E. Lessons from the application in this setting of the IV research design from the immigration literature

In this Appendix, I show in detail the lessons from the Venezuelan-to-Peru immigration case to apply two standard instruments used in the immigration literature. Overall, I show that the sudden Venezuelan net inflow in Peru is so sharp and extraordinary that the share of Venezuelans in the past does not have sufficient variation to predict the most recent arrival of immigrants to Lima and Callao.

### 2. Different measurements for networking instrument to predict the immigration inflow locations

In the current immigration literature, it is common to use the networking idea where the immigrants in the destination country influence the location of the new immigrants (Adão et al., 2019; Altonji & Card, 1991; Borusyak & Hull, 2020; Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018a). Under the exclusion restriction that this geographic distribution does not affect the natives' labor market outcomes, one can estimate the causal effect of immigration on natives' employment and wages.

#### *2.1.1. First-stage: A Simple Measure of The Net Influx of Venezuelans in 2018 on The Past Distribution of Venezuelans*

Following Monras (2020), I can instrument the current inflow of Venezuelans in 2018 with the share of Venezuelans from previous years and data sources. Formally, the first stage is as follows:

$$\Delta Share2018_d = \alpha + \beta \times Share(t-1)_d + X_d \times \gamma + \varepsilon_d \qquad (5)$$

Where $\Delta Share2018_d$ is the net inflow of Venezuelans in 2018,[25] $Share(t-1)_d$ is the past share of Venezuelans in $t-1$ district $d$, $X_d$ are control variables by district $d$, and $\varepsilon_d$ is the error term. I denote the past share with $t-1$ because I can use the share in 2007, 2016, or 2016 from the different data sources. Intuitively, the past share of Venezuelans should affect the current labor market outcomes only through the channel of the change in Venezuelan share.

To estimate the net inflow of immigrants in 2018 using the share of Venezuelans in the previous year, I exploit two data sources: the Venezuelan Survey (ENPOVE) and the Peruvian Labor Force Survey (LFS), as described in section 4. First, from the Venezuelan Survey, I use the number of

[25] Formally, the net inflow definition in this equation is the difference by the end of 2017 with 2018:

$$\Delta Share2018_d = Share2018_d - Share2017_d$$

Venezuelans in 2016 and 2017 to measure the share of Venezuelans in those years following the equation (4) definition. Hence, I combine both surveys to create the past settlement shares until 2017 to predict the inflow in 2018. Second, I use the Census data in 2007 and 2017 to measure equation (4) in those two years. Therefore, I have four different past shares of Venezuelans from two data sources to use as an instrument to predict the net inflow in 2018.[26]

Using the Census data, the main lesson from the spatial distribution of Venezuelans 10 years ago does not predict where the current inflow will be. Table B.4. in Appendix B shows the estimates of the first stage in equation (5), and Figure A.7 in Appendix A illustrates these estimations with the partial correlations. Table B.3 shows four potential instruments to demonstrate that the past share using the Census 2017 is the best instrument. Columns (1) and (2) use the shares of Venezuelans from the Venezuelan survey and LFS in 2016 and 2017, respectively. Columns (3) and (4) use the Census in 2017 and 2007, respectively. While the share of Venezuelans using the first set of data sources has a higher F-statics of 79, the share calculated with the Census 2017 has more observations to predict the net inflow of Venezuelans. The average share of Venezuelans in 2007 of 0.03% is too small to predict the most recent influx of 4.05% between 2016 and 2018. The problem with this instrument is that it uses a negligible percentage to predict a wide range of non-zero values.

The arrival of Venezuelan-born immigrants, especially in 2018, is large, sharp, and unprecedent; therefore, the spatial variation of Venezuelans before is not enough to predict the net changes at the district level. Overall, the net inflow of Venezuelans in 2018 was 3.5 times the share of Venezuelans in 2017 obtained from the Census. The latter is also consistent with the more than 5-percentage point increase from 1% to 6.2% share of Venezuelans in Figure 4. To illustrate, I use two districts in Lima as leading example of the first-stage prediction problem in Table B.5. Lima and Surquillo had a ratio of Venezuelan to working-age population of 0.0004 in 2007 from the Census data. There is not enough variation between districts to predict a change of 0.09 and 0.13, respectively, in 2018. Therefore, the first stage problem is trying to use almost zero shares to predict a large range of non-zero positive numbers.

[26] See Appendix D, for more detail on limitation and comparision among data sources for the past share of Venezuelan immigrants measurements.

### *2.1.2. Two Shift-share instruments: using the city of origin and the enclave shares from the Census*

To estimate the first stage in equation (5), I also use two different definitions of the shift-share instrument to use other sources of variation to measure the past settlement of Venezuelans. First, I exploit the variation from the city of origin from the Venezuelan Survey (ENPOVE) to compute the shift-share instrument. Then, I use a traditional enclave share with the information from the Census as a second shift-share instrument.

To exploit the information about the state of origin in Venezuela from the Venezuelan Survey (ENPOVE), I follow Card's (2009) notation and definition of the shift-share instrument using the city of origin of immigrants:

$$\widetilde{m}_d = \sum_o \frac{M_{od}}{M_o} \frac{\Delta M_{o2018}}{L_d} \qquad (6)$$

Where $\frac{M_{od}}{M_o}$ is the share of immigrants from origin o in Venezuelan, $\Delta M_{o2018}$ is the number of new arrivals to Peru in 2018 at the national level, and $L_d$ is the normalization of the local population at the district level in 2017.

I exploit the information about the immigrants' city of origin from the Venezuelan Survey (ENPOVE) to compute the shift-share in equation (6). The Venezuelan survey has information at the state and municipality levels. I use the state level to minimize sampling problems from the reporting at the municipality level because 63 out of the 199 states have five or fewer observations. In Table B.6. I show the percent of the sample from de Venezuelan survey (ENPOVE) by the state of origin in Venezuela. Notice that 50% of the sample is from the five states of Caracas (capital), Carabobo, Lara, Zuli, and Aragua. So, I use this variable measure for the respondent that arrived in Peru in 2016 and 2017 as the enclave share $\frac{M_{od}}{M_o}$, and the aggregate inflow of Venezuelans is also from the Venezuelan survey. Finally, I use the Labor Force Survey to calculate the working wage population by district $L_d$ similar to equation (4).

The second shift-share measurement exploits the information from the Census in 2017 and 2007 differently. I follow Delgado-Prieto (2022) definition:

$$Shiftshare_d = \left(\frac{Venezuelan_{dt}}{Venzuelan_t} \times \Delta Ven_{18}\right) / L_{d17} \qquad (7)$$

Where $Venezuelan_{dt}$ is the number of Venezuelans in district $d$ year $t$, $Venezuelan_t$ is the total number of Venezuelan immigrants in year $t$, $\Delta Ven_{18}$ is the aggregate inflow of Venezuelan-born immigrants in 2018 to Peru, and $L_{d17}$ is the working-age population in district $d$ in 2017 to normalize with the same baseline as the share of Venezuelans in equation (4).

I use the Census data and the Venezuelan Survey to calculate this second shift-share definition. I calculate the enclave shares $\frac{Venezuelan_{dt}}{Venzuelan_t}$ and the working-age population $L_{d17}$ from the Census data in 2007 and 2017. I use the Venezuelan Survey to compute the aggregate inflow of Venezuelan to Peru in 2018 $\Delta Ven_{18}$, again as the difference between the stock of immigrant-born in 2017 and 2018.

The two shift-share definitions show a low prediction power of the significant net inflow of Venezuelan immigrants in 2018. In Figure A.7. from Appendix A, I present the partial correlations of the change in the Venezuelan share in 2018 on these two instruments measured in different periods. Notice again that the information from the Census 2007 reveals that there were few Venezuelan-born immigrants to predict their location decision in 2018. The shift-share with the highest correlation with the 2018 immigrant inflow is the one that exploits the city of origin variation from ENPOVE when using the stock of immigrants up to 2017.

To estimate the first stage in equation (5), I also use two different definitions of the shift-share instrument to use other sources of variation to measure the past settlement of Venezuelans. First, I exploit the variation from the city of origin from the Venezuelan Survey (ENPOVE) to compute the shift-share instrument. Then, I use a traditional enclave share with the information from the Census as a second shift-share instrument.