# The Short-Term Labor Market Impact of Venezuelan Immigration in Peru*

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**Abstract**

Peru is the second-largest recipient of Venezuelans worldwide. We estimate the effect of the arrival of Venezuelan migrants in Peru as of the end of 2018 on the labor market outcomes of natives, using a skill-cell IV methodology. The initial regression analysis exploits the variation in supply shifts across education-experience groups over time. It indicates that immigration had no adverse impact on native wages. However, the paper highlights that immigrants and natives with similar education and experience are likely to work in different occupations. The subsequent analysis based on occupational clustering confirms the null effect on wages and indicates that a 10% increase in immigrants decreased formal employment by 1.5% and had little to no effect on hours of work. We report evidence in favor of immigrants being close substitutes to the least productive natives, suggesting that firms substituted native formal labor for low-cost immigrant informal labor.

**Keywords:** Immigration, education-experience cells, occupation cells
**JEL Classification:** F22, J21, J24, J61.

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# 1 Introduction

According to the United Nations High Commissioner for Refugees (UNHCR 2022), over 6 million Venezuelans now live abroad, making the Venezuelan migrant crisis one of the largest displacement crises in the world and the largest external displacement crisis in Latin America's recent history. The vast majority of Venezuelan migrants have chosen Latin American countries as their destination and Peru constitutes the second largest Venezuelan migrant hosting nation, with 1 million Venezuelans as of the end of 2020, representing about 3.7% of Peru's urban population and 8% of the urban labor force.[1] This paper studies the short-term impact of Venezuelan migration on natives' labor market outcomes. We show that the inflows of Venezuelans in Peru do not adversely affect wages and barely increase hours of work but lead to the displacement of local workers out of formality.

A key issue in the literature on the impacts of migration is the identification of native groups who are most likely to be affected by the migrant shock. Two approaches have been taken. The spatial approach estimates regional effects by defining local markets geographically and exploiting the variation in the number of immigrants across regions. Studies relying upon this methodology have usually found that migration had little or no effect on the labor market opportunities of native workers.[2] The spatial approach has since been criticized most notably by Borjas (1994), Borjas et al. (1992), and Borjas et al. (1996), who pointed out that immigration's impact will not be observable along the geographic dimension because any incipient local effects will be diffused by the migration of native workers out of the high-immigration cities, by capital inflows into them, or by intercity trade.

In light of these problems, a growing body of literature adopted the skill-cell approach, which identifies the impact of immigration at the national level on the basis of qualification groups. This approach, pioneered by Borjas (2003), uses education and labor market experience as indicators of skills and assumes that immigrants and natives belonging to the same education and experience groups are perfect substitutes. Borjas (2003) finds that higher immigrant inflows between education and experience groups are negatively associated with the wages of male natives, particu-

[1] Calculations by the authors using data by the Peruvian Household Survey and the Inter-Agency Coordination Platform for Refugees and Migrants from Venezuela (`https://www.r4v.info/en/refugeeandmigrants`, last retrieved on the 28th of September of 2022).

[2] See Altonji and Card (1991), Borjas (1987), Card (1990), Goldin (1994), Grossman (1982), LaLonde and Topel (1991), and Schoeni (1997).

larly for workers who did not attend college. More recent studies moved away from the education-experience group in view of the evidence of imperfect substitutability between immigrants and natives within education groups (Card 2009; Dustmann et al. 2012; Dustmann and Preston 2012; Manacorda et al. 2012; Ottaviano and Peri 2012). Alternative criteria to define labor markets are occupations (Cohen-Goldner and Paserman 2011; Friedberg 2001; Orrenius and Zavodny 2007; Steinhardt 2011)[3] and combinations of occupations with the district of residence and industry (Cohen-Goldner and Paserman 2011) and with experience (Sharpe and Bollinger 2020).

This study estimates the short-term effect of Venezuelan immigration inflows on the Peruvians' labor market outcomes using the novel Survey for Venezuelans Living in Peru (henceforth, ENPOVE) and Peru's National Household Survey (henceforth, ENAHO). We adopt a skill-cell approach and argue that immigration does not adversely affect natives' earnings but displaces natives from the formal sector. We develop our conclusion in three stages. First, we use the variation of Venezuelan workers' shares within education-experience cells over time and find no significant effects of immigration on wages. Second, the analysis is extended to the level of occupations based on the observation that in Peru, immigrants and natives work in different occupational segments despite having similar education and experience. We rely on information about immigrants' former occupations, as in Friedberg (2001), to address the endogeneity in occupational choice and confirm the null effect on wages. Third, we inquire whether the local labor market adjusted through changes in employment and find that a 10% increase in immigration decreases formal employment by 1.5%, has little to no effect on hours of work, and has no effect on informal employment. Importantly, these estimates are robust to changes in the baseline period, to different transformations of the dependent and independent variables, and cannot be replicated by placebo experiments.

Our study offers several contributions to the literature. First, we use unexplored data on migrants that capture both regular and irregular migrants, contrasting with earlier studies that mostly relied on documented migrants.[4] Restricting the foreign

[3]While the works by Cohen-Goldner and Paserman (2011), Orrenius and Zavodny (2007), and Steinhardt (2011) use the occupation criteria because they observe that migrants and natives are not substitutable at the education level, Friedberg (2001) uses occupation to exploit a novel instrumental variable in her data: immigrants' occupations in their country of origin.

[4]Orrenius and Zavodny (2007) and Carrasco et al. (2008) use data describing only legal migrants while Steinhardt's (2011) data only include migrants covered by social security; Broussard (2017) uses census data that do not certify the full count of illegal migrants. An exception is Sharpe and Bollinger (2020), whose data contain information about both legal and illegal immigrants.

sample to only regular migrants might not capture the full extent of competition in the labor market. Irregular migrants not only work, but they also do so in low-paying jobs, which raises concerns about potential displacement effects for the most vulnerable natives.[5] Moreover, ENPOVE data allow us to expand the set of exogenous sources of variation for migration. Our data contain information about the employment status of immigrants in their country of origin, a variable that has not been used since Friedberg (2001) mainly due to data limitations. Thus, we revisit the use of pre-migration employment distribution as a potential instrument to address the endogeneity problem inherent in any empirical work on migration.

Second, we add to the scarce literature on the effects of migration in developing countries, which usually have weaker labor markets and institutions. Empirical evidence yields mixed results. Research on the Syrian migration to Turkey finds null effects on wages, alongside with negative effects on informal employment and positive effects on formal employment (Aksu et al. 2022; Ceritoglu et al. 2017; Del Carpio and Wagner 2016; Tumen 2016).[6] These studies, however, report contrasting results regarding changes in employment composition. While Del Carpio and Wagner (2016) and Aksu et al. (2022) report that Turkish workers occupational upgraded from informal to formal jobs, Tumen (2016) and Ceritoglu et al. (2017) find that most of the men who lost their informal jobs remained unemployed. On the other hand, evidence on migration in Spain finds a null effect on wages and employment (Carrasco et al. 2008), and research on migration in South Africa reports negative effects on native wages and displacements from informal jobs toward formal jobs (Broussard 2017).

To date, there has been little agreement on the effects of Venezuelan migration on the labor market in the hosting economies. There is evidence for negative wage effects mostly concentrated on less-educated and informal workers in Colombia (Caruso et al. 2021; Delgado-Prieto 2022; Lebow 2022b; Peñaloza-Pacheco 2022), Ecuador (Olivieri et al. 2022) and Peru (Asencios and Castellares 2020; Morales and Pierola 2020). Some studies find a little-to-no effect on native employment (Lebow 2022b; Olivieri et al. 2022), while others provide evidence that Venezuelan migration leads to increases in employment for locals (Groeger et al. 2022; Morales and Pierola 2020) or

[5]See Böhme and Kups (2017) and Kossoudji and Cobb-Clark (2002) for literature on the effect of legal requirements on immigrants' access to jobs.

[6]The negative wage effect reported by Aksu et al. (2022) corresponds to salaried employment, as Ceritoglu et al. (2017). Once Aksu et al. (2022) account for self-employment, the overall wage effect is null. The negative wage effect in Del Carpio and Wagner (2016), on the other hand, includes salaried and self-employment.

job displacements (Peñaloza-Pacheco 2022).[7] Our findings are in line with more recent Peruvian evidence indicating that migration had no detrimental effect on wages (Boruchowicz et al. 2021; Groeger et al. 2022) and with Delgado-Prieto (2022) and Lebow (2022b) regarding job displacements in the formal sector that seem to be driven by the substitution of informal migrant labor for formal native labor. We further provide evidence that migrants are overrepresented at the bottom of the native wage distribution, suggesting that native workers most likely to be displaced are those employed in low-paying occupations.

The case under study differs from other migration episodes in many areas. First, Peru has a larger informal sector than other host countries.[8] The informal sector has no minimum wage and tends to have high turnover rates, increasing wage flexibility. Second, Venezuelan migrants and Peruvian natives speak the same language and have a similar cultural background, which increases their substitutability in the workforce and suggests downward pressure on wages as migrants and natives are less likely to specialize in different tasks. Finally, despite Venezuelan migrants being more educated than the Peruvian workforce, they are overrepresented in the informal sector. The Peruvian case is also distinct from that in Colombia, which has received considerable attention in the emergent literature studying the economic effects of Venezuelan migration. To the extent that the Venezuelan migration in Colombia consists of a mixed population of Venezuelans and Colombian returnees, the Venezuelan migration in Peru represents a purer labor supply shock.[9]

The rest of the paper is organized as follows. In Section 2, we provide some background on Venezuelan immigration in Peru. Section 3 presents the data used in the analysis and Section 4 describes the employment trends of migrants in the Peruvian labor market. In Section 5, we outline our identification strategy. Section 6 presents the results and a series of robustness tests, and is followed by a discussion

[7] These effects, however, are not homogeneous among natives. For Ecuador, Olivieri et al. (2022) do not find any effect on natives' labor market outcomes but identify deterioration of employment quality and earnings among young and low-educated natives in high immigration regions. For Peru, the gains in employment reported by Morales and Pierola (2020) are observed for natives with tertiary education.

[8] Informality in Turkey during Syrian migration was around 35% (Del Carpio and Wagner 2016, Table 1, p.50; Ceritoglu et al. 2017, p.4). Informality for males and females in South Africa was 25% and 41%, respectively, during the migration period (Broussard 2017, Table 4, p.401). 62% and 48% of urban workers in Peru (INEI, Estadísticas) and Colombia (DANE 2019), respectively, held an informal job in 2018.

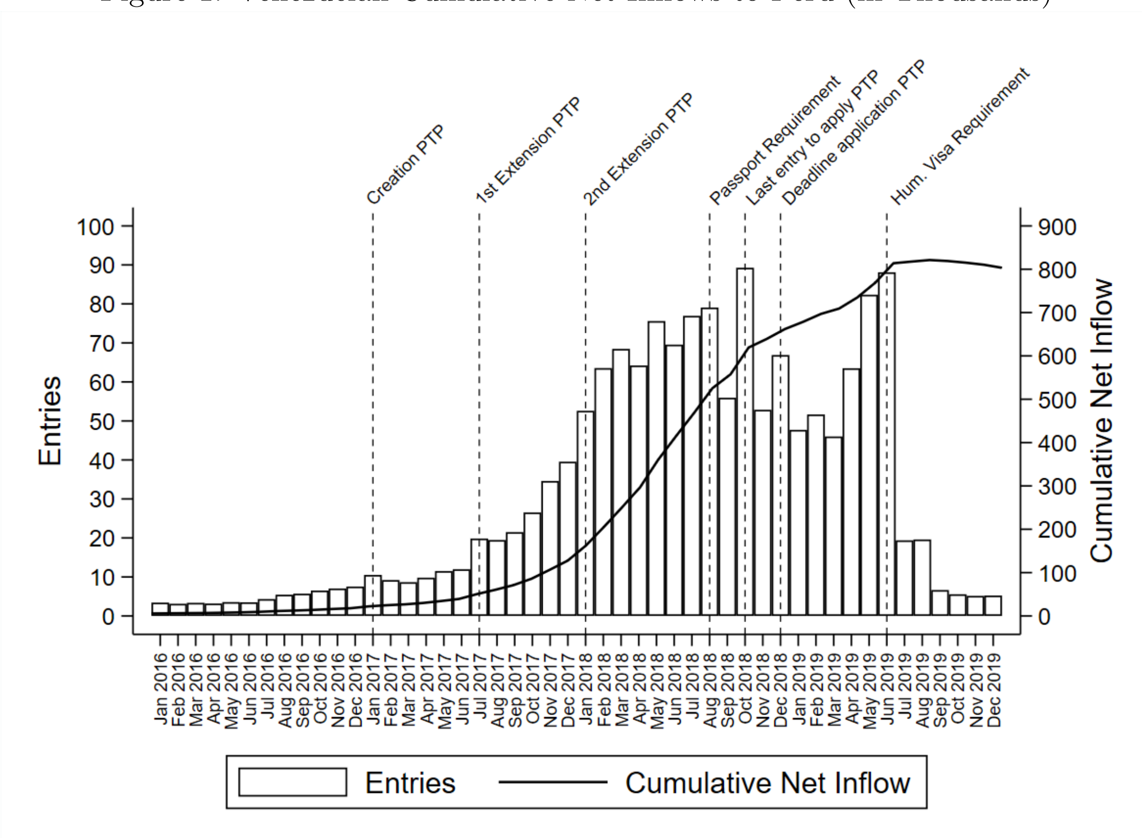
[9] By 2018, approximately 28% of migrants from Venezuela to Colombia are return migrants, i.e., Colombian-born citizens who migrated during the 80s and 90s to Venezuela attracted by the oil boom (Bonilla-Mejía et al. 2020).

of our findings in Section 7. Section 8 concludes.

## 2 Venezuelan Immigration in Peru

The pattern of Venezuelan migration to Peru over the period 2016-2019 is presented in Figure 1. Since 2016, immigration has risen sharply as a result of the economic, social, and political crisis facing Venezuela. At the peak of the wave, 90 000 Venezuelans immigrated to Peru in a single month. Figure 1 shows that, as conditions in Venezuela deteriorated, Venezuelan migrants settled in Peru instead of just passing through the country. Taking December 2016 as a benchmark, the accumulated migratory balance increased tenfold in December 2017; and multiplied by a factor of 54 and 66 in December 2018 and 2019, respectively.

Figure 1: Venezuelan Cumulative Net Inflows to Peru (in Thousands)




Source: Superintendencia Nacional de Migraciones in Peru.

The migration patterns in Figure 1 reflect the reactions to Peru's institutional response, which had two well-defined stages. Until the end of 2018, Peru implemented an open-door policy. Peru not only allowed Venezuelans to enter the country with either identity cards or (expired) passports but also was the first country in the region to create a specific permit that regularized their migration status: the Temporary Residence Permit (PTP). This document granted Venezuelans the right to live and legally be employed in Peru for one year, with the option to renew the permit. The sudden increase in the number of entries in January 2017, July 2017, and January 2018 respond, respectively, to the PTP's creation and its two extensions.

As migration intensified, Peru made a stark restrictive shift. The first measure was the introduction of the passport requirement for anyone entering Peru from August 2018 on, which explains the drastic decrease in Venezuelan entries observed in the following month. This measure, however, was the subject of a lawsuit brought by the National Human Rights Coordinator, was initially revoked in October 2018, and then became effective again in the same month, in response to an appeal filed by the government. The second measure was establishing earlier deadlines for applying for the PTP and for entering the country in order to be eligible for the PTP, i.e. December 2018 and October 2018, respectively.[10] Thus, the abrupt increase of entries in October 2018 responds to both the revoking of the passport requirement and the setting of the end of that month as the entry deadline to be eligible for the PTP. Finally, in June 2019, Peru announced the implementation of a humanitarian visa as an entry requirement. As a result of these changes in institutional arrangements, the accumulated migratory balance grew by 904% between 2016 and 2017, 438% between 2017 and 2018, and only by 22% by 2018 and 2019. This paper considers Venezuelans who arrived in the period 2016-2018, in which Peru exhibited a lenient policy towards Venezuelan immigration.

The Venezuelan migration is distinct from other episodes studied in the literature in that the profile of migrants varied across receiving countries, as well as over time within countries. The reports of the IOM Displacement Tracking Matrix (DTM) for countries in Latin America and the Caribbean indicate that Venezuelans who migrate to the Andean countries (including Peru) are less educated than those who migrate to Central America and the Southern Cone of America. It follows that, due to their socioeconomic profile, the first group make part of their trip by bus, boat, and/or foot, while the latter group were able to make all or part of the trip by plane.[11]

[10] The previous PTP application deadline was June 2019, and the deadline for entering the country was December 2018 (Supreme Decree 007-2018-IN).

[11] The Displacement Tracking Matrix (DTM) are surveys of people over 18 years old that are

Our data exhibits such variation in the period of analysis. Whereas 31% of Venezuelan migrants who entered in the first quarter of 2016 hold a bachelor's degree, that percentage drops to 23% and 18% for those who entered Peru in the last quarter of 2017 and 2018, respectively. Consistent with this pattern, travel by air was far more common among Venezuelan migrants arriving in Peru in 2016 relative to their peers arriving in 2018 (32% and 4%, respectively). Almost nine out of ten migrants arriving in 2018 traveled by bus, whereas among those arriving in 2016, only half did so. The heterogeneity in immigrants' educational profiles across time observed in our data is crucial to identify the causal effect of migration flows on native labor markets, as explained in Section 6, particularly in our analysis based on education and experience.

# 3 Data

Our data are drawn from two different surveys. First, 2016-2018 ENAHO Surveys, divided into quarterly subsamples.[12] Second, the ENPOVE Survey, which was implemented in the last quarter of 2018 and captures information about a random sample of 9,847 Venezuelan immigrants living in the cities with the largest numbers of immigrants (Lima and Callao, Tumbes, Trujillo, Cusco, and Arequipa). Taken together, these cities host 85% of all Venezuelan immigrants in Peru, and thus, this survey is representative of Venezuelan immigrants in the country (INEI 2019).

We limit the sample to men aged 17-64 who are employed with positive wages in urban labor markets and who have 1-40 years of experience, although we also provide results for samples that include women.[13] We further restrict the native sample to individuals born in Peru, and we calculate the number of natives and immigrants by expanding the ENAHO and ENPOVE with their sampling weights.

ENPOVE data offer several advantages compared with data used in other migration studies. First, the data consist of both documented and undocumented Venezuelans. The inclusion of undocumented migrants is relevant in developing economies

carried out at border points and destination cities. See Reports in `https://dtm.iom.int/reports`

[12]Our quarterly subsamples were prepared by INEI on request. They differ from the downloadable files at INEI's microdata library in two aspects. First, they include variables for informality and imputed earnings as well as work hours. Second, they include missing records that were recovered throughout the year. For robustness analysis, we also use the 2015 ENAHO.

[13]Women are excluded in the main sample because they face more periods of inactivity or unemployment, such that the correspondence between their potential and effective experience tends to collapse.

where informal employment is widespread and represents an available alternative to avoid institutional barriers to formal employment (Blouin 2019).[14] In this context, irregular migrants are inclined toward informal employment and thus increase the risk of displacement for natives employed in that sector. Second, ENPOVE data capture information about Venezuelans who stayed in Peru at least until the last quarter of 2018. Thus, we arrive at a more precise count of migrants than do studies relying on data on Venezuelan migration flows, which could skew the actual counts due to multiple entries and exits as well as the overlooking of migrants who enter through unofficial points. Third, ENPOVE data capture the former occupation migrants had in Venezuela, which allows us to account for the endogeneity of occupational choices in Peru in our analysis based on occupations. Finally, Venezuelans captured in ENPOVE represent the early stage of the Venezuelan migration in Peru. Most of them arrived between 2016 and 2018, a period in which Peru had a receptive response toward migrants in terms of entry and work permits (PTP). Thus, our immigrant sample represents a labor supply shock composed of an immigrant population equally eligible for work permits.

However, our data are not exempt from limitations. ENPOVE data capture information about Venezuelans in Peru at just a single point of time: the last quarter of 2018. Ideally, we would have repeated cross-sections for both locals and migrants, as most studies using the skill-cell approach do. These ideal data allow researchers to obtain counts of locals and migrants at different points of time. We use the date of arrival to assign migrants to quarters between 2016 and 2018 to circumvent that limitation. Counts in every quarter are then obtained from the created cross-section samples.[15] Date of birth is used to calculate migrants' ages at every quarter, and we assume that the educational level they report at the Survey time is the same educational level they had at the time of their arrival in Peru.[16] Thus, the variability in immigration across cells and time in the analysis based on education and experience is given by changes in the population and age structure of migrants.

[14]In our data, only 2.2% of Venezuelans report not having registered at an official entry point. However, we believe this figure is underestimated because of fear of deportation.

[15]In Appendix Figure A1, we compare the number of migrants in every quarter calculated with ENPOVE and the administrative data on net migration flows provided by the Superintendencia Nacional de Migraciones. We find that the trends are similar, and we take this as a proof that our migrant counts are a close approximation of the stock of migrants living in Peru at different quarters.

[16]Raw data indicate that less than 1% of Venezuelans are enrolled in the Peruvian education system, which makes realistic our assumption that immigrants' education level has remained invariant between their arrival time and the Survey time.

The single cross-section nature of ENPOVE data imposes more restrictions in the analysis based on occupations. The assumption that immigrants' occupations remain time-invariant after arriving in Peru is implausible. The prevalence of informal employment in the Peruvian labor market, as well as Peruvians and Venezuelans sharing the same language, facilitate occupational mobility. Thus, we follow Friedberg (2001) and adopt a first difference approach by setting the first quarter of 2016 as the baseline period (in which migration is set to zero) and the last quarter of 2018 as the endline.[17]

Logs of deflated gross monthly wages for all workers with positive wages are used to measure earnings. We deflate earnings using the Consumer Price Index with the base period being 2009. Informal employment is defined following INEI's criteria as described in *Cuenta Satélite de Economía informal 2007-2016*. Employers and self-employed workers whose business units belong to the informal sector, wage earners without employer-financed social security, and unpaid family workers are all labeled as informal workers. Logs of reported hours worked in a given week for the main occupation are used to measure hours of work.

For the analysis based on education and experience, we classify persons into four education groups and 5-year experience groups. Each combination of education and experience represents a skill group so we end up with 32 skill groups in every quarter, resulting in 384 observations (4 education groups, 8 experience groups, and 12 quarters). We consider four education groups: no high school completion, high school completion (including some years of technical education), technical education completion (including some years of college), and college completion.[18] As is customary in this literature, we calculate potential experience based on educational attainment. It is assumed that workers without a high school diploma enter the labor market at 14, high school graduates and persons with some technical education enter the labor market at 17, technical education graduates and persons with some college enter the labor market at 19, and those with a college degree enter the labor market at 23.[19] The immigration variable is constructed by combining ENAHO and ENPOVE data and is defined as the ratio of immigrants to total employment.

[17] The presence of immigrants in Peru was negligible at the beginning of 2016. In our sample, less than 4% of Venezuelans had arrived in Peru by that date.

[18] Educational degrees in Peru and Venezuela do not share the same denominations. In Appendix Table A1 we present the recoding of Peruvian and Venezuelan educational categories.

[19] We use the 2018 ENAHO to calculate the age of labor market entrance in a sample of recent graduate individuals younger than 40 and who live in urban areas.

The analysis based on occupations relies on the civilian sample that is employed with positive wages and a valid occupational code. Owning to the data limitations described above, we only use the 2016-I and 2018-IV periods. We define occupations by using a two-digit code, based on the 1988 International Standard Classification of Occupations (ISCO88). These occupational groups capture the set of occupations for which immigrants who report working in a particular occupation are likely to be substitutable for natives, and thus these groups address bias arising from the possibility that natives change occupations in response to immigration.[20] In this analysis, we rely only on ENPOVE data to construct our immigration variable, which is given by the log of the number of migrants employed in each occupation.[21] We have valid data for 60 occupations in both periods.

# 4 Descriptive Results

Table 1 describes the native sample, extracted from ENAHO, and the immigrant sample, extracted from ENPOVE.

[20]Alternative aggregations may not accurately capture the competition between workers in a cell. For instance, if we define cells using 3-digit occupational codes, we would be assuming that metallurgical engineers (code 224) and mining engineers (code 225) do not compete. Using 1-digit occupational codes assumes that physicians and accountants compete as both are in the same major group, number 2. Two-digit codes aggregate both kinds of engineers under code 22 but separate physicians (code 23) from accountants (code 25).

[21]Using a ratio to measure immigration requires relying on two different data to construct both the endogenous and instrument variables (ENPOVE for the numerator and ENAHO for the denominator). We did not find the instrument to be relevant when the immigration variable is defined as a ratio. On the other hand, the instrument is relevant when the immigration variable is measured in (log) levels.

Table 1: Profile of Natives and Venezuelan Immigrants in Peru, 2018

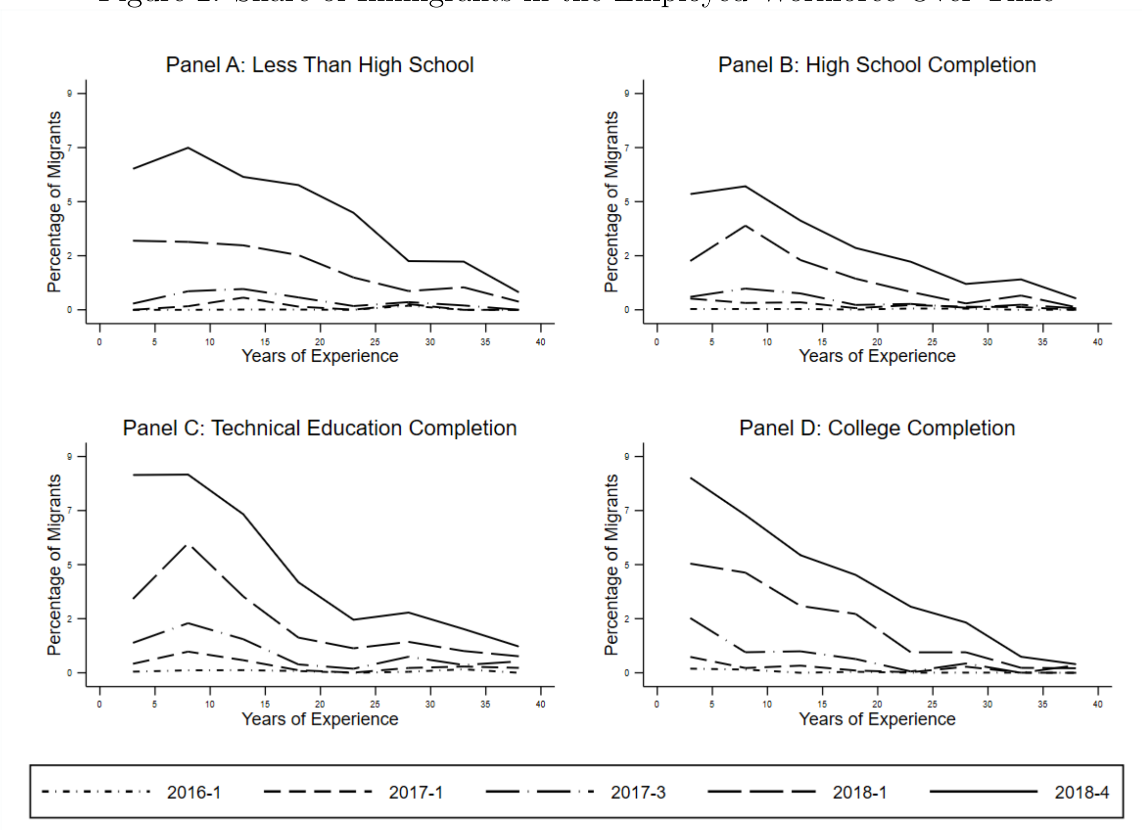
| | Peruvians | Venezuelans |
|---|---|---|
| Age | 37.52 | 30.83 |
| | (11.22) | (8.18) |
| Years of experience | 19.73 | 12.51 |
| | (11.34) | (8.32) |
| Education groups | | |
| Less Than High School | 0.21 | 0.17 |
| | (0.41) | (0.37) |
| High School Completion | 0.40 | 0.33 |
| | (0.49) | (0.47) |
| Technical Education Completion | 0.22 | 0.29 |
| | (0.42) | (0.46) |
| College Completion | 0.16 | 0.21 |
| | (0.37) | (0.41) |
| Monthly Wage | 981.17 | 878.75 |
| | (986.79) | (433.78) |
| Informal Worker | 0.60 | 0.88 |
| | (0.49) | (0.33) |
| Weekly hours worked | 46.45 | 61.89 |
| | (18.01) | (17.07) |
| Observations | 4,062 | 3,790 |

Notes: Means are presented, SDs are in parentheses. The data come from the 2018-IV ENAHO and ENPOVE. The samples are restricted to men aged 17-64 who are employed with positive wages in urban labor markets and who have 1-40 years of experience. Monthly wages are workers' gross income expressed in 2009 PEN (local currency). A Venezuelan worker is an informal worker if she is a salaried employee without a contract.

The average immigrant is younger and therefore has less labor market experience than the average native. The most notable characteristic of Venezuelan immigrants is their high level of education. Over 83 percent of male Venezuelan immigrants had completed high school, and half of them have completed tertiary technical education or have some years of college. The share of Peruvian high school graduates, on the other hand, is 79 percent, and only 38 percent of Peruvians have completed tertiary technical education or have some years of college. Furthermore, despite immigrants being more educated than natives, they have worse labor market outcomes. For example, the share of workers with an informal job is higher for the group of Venezuelans compared to that of natives. Accordingly, monthly wages are lower within the group of Venezuelans. An average work week for a Venezuelan and Peruvian worker consists of, respectively, 62 and 46 hours.

Figure 2 illustrates the evolution of immigrant labor supply shocks over time for different groups of education-experience and selected quarters between 2016 and 2018. Each panel within Figure 2 corresponds to a group of education and experience classifications described above. Panel A presents data for the lowest educational group. As we progress through Panels B-D, the level of education increases.

Figure 2: Share of Immigrants in the Employed Workforce Over Time




Notes: Each panel presents the average male immigrant share across potential experience groups in the corresponding education group. Panel titles have been simplified to facilitate visibility (Panel B includes some years of technical education and Panel C includes some years of college). Selected quarters are shown for the period 2016-2018. We use the midpoint of each potential experience group to illustrate the trends in immigrant shares across groups

In 2016 and the first quarter of 2017, the immigrant share was similar across experience groups. In 2018, the immigrant share was high for less experienced skill groups but low for groups with more experience. There is one notable difference across the four panels: immigrants comprise a significantly larger share of highly educated workers, particularly within younger groups. In Panels C and D, immigrants made up 8% of the overall labor supply for workers with less than 5 years of experience. In contrast, immigrants comprise only 6% and 5% of inexperienced high school dropouts (Panel A) and high school graduates (Panel B), respectively. Another difference across the four panels is that, as workers age, the share of migrants diminishes consistently for the most educated (Panel D). However, the share of migrants for the less educated groups has a shift among the oldest workers within these groups (Panels A, B, and C).

The validity of using education and experience to define labor markets hinges on the assumption that for a given education group, immigrants and natives with similar levels of experience are closer substitutes than immigrants and natives who differ in their experience. One way to test this assumption is by investigating whether natives and immigrants with similar education levels work in different occupational segments, an approach also taken, for example, by Borjas (2003), Manacorda et al. (2012), and Steinhardt (2011).

We use the Duncan index (Duncan and Duncan 1955) of dissimilarity to compare native and migrant occupational distributions, holding education constant. This index captures the proportion of either group that would need to change occupations to make the two distributions equal. The index goes from 0 to 1, taking the value of 0 when immigrants and natives have identical occupational distributions, and taking the value of 1 when the two groups are segregated in completely different occupations. Thus, the smaller the index, the more similar the occupational distributions and the higher the substitutability.

We classify workers into 2-digit occupation codes, aggregate workers into ten-year experience bands, and restrict the analysis to workers in nonmilitary occupations. Table 2 reports the calculated index for each of the education groups.

Table 2: Duncan Index of Dissimilarity for Natives and Venezuelan Immigrants in Peru, 2018

| Education-Experience of native groups | Experience of corresponding immigrant group | | | |
|---|---|---|---|---|
| | 1-10 years | 11-20 years | 21-30 years | 31-40 years |
| Panel A: Less Than High School | | | | |
| 1-10 years | 0.525 | 0.443 | 0.485 | 0.607 |
| 11-20 years | 0.505 | 0.399 | 0.488 | 0.598 |
| 21-30 years | 0.560 | 0.437 | 0.468 | 0.565 |
| 31-40 years | 0.547 | 0.394 | 0.418 | 0.500 |
| Panel B: High School Completion | | | | |
| 1-10 years | 0.366 | 0.325 | 0.356 | 0.618 |
| 11-20 years | 0.461 | 0.324 | 0.346 | 0.596 |
| 21-30 years | 0.484 | 0.335 | 0.346 | 0.608 |
| 31-40 years | 0.422 | 0.341 | 0.336 | 0.589 |
| Panel C: Technical Education Completion | | | | |
| 1-10 years | 0.446 | 0.538 | 0.478 | 0.742 |
| 11-20 years | 0.527 | 0.610 | 0.557 | 0.672 |
| 21-30 years | 0.443 | 0.533 | 0.495 | 0.677 |
| 31-40 years | 0.545 | 0.602 | 0.563 | 0.675 |
| Panel D: College Completion | | | | |
| 1-10 years | 0.741 | 0.724 | 0.769 | 0.854 |
| 11-20 years | 0.681 | 0.663 | 0.704 | 0.764 |
| 21-30 years | 0.769 | 0.726 | 0.772 | 0.899 |
| 31-40 years | 0.765 | 0.695 | 0.734 | 0.826 |

Notes: Within each education group, the index is calculated separately for each pair of native and immigrant groups. The data come from the 2018-IV ENAHO and ENPOVE. The samples are restricted to men aged 17-64 who are employed with positive wages in urban labor markets and who have 1-40 years of experience. Panel titles have been simplified to facilitate visibility (Panel B includes some years of technical education and Panel C includes some years of college)

For all education-experience cells, the indices are in the region 0.32-0.89, implying that between 32% and 89% of immigrants (or natives) would have to change jobs to equalize the occupational distribution of employment. These values are much larger than those reported in studies concluding that migrants and natives are substitutes within education and experience cells (Breunig et al. 2017) and within education and age cells (Manacorda et al. 2012), suggesting that it is plausible to think of Peruvians and Venezuelans as being imperfect substitutes within education-experience cells.

Consider the group of native workers who are high school dropouts and have fewer than ten years of experience. The index of dissimilarity with immigrants who have the same experience is 0.525. This index decreases to 0.44 for immigrants who have 11 to 20 years of experience, and to 0.485 for immigrants with 21 to 30 years. Similarly, consider the native workers who have technical education or some years of college and have 31 to 40 years of experience. The index of dissimilarity with immigrants who have the same experience is 0.675, but this index falls to 0.60 for immigrants who have 11 to 20 years of experience, to 0.563 for immigrants who have 21-30 years, and to 0.545 for immigrants who have less than 10 years. In sum, the occupation distributions of immigrants and natives with different experience levels are generally more similar than the distributions of immigrants and natives with the same levels of experience.

Table 2 thus suggests a degree of imperfect substitutability between immigrants and natives within education-experience skill groups. One factor that may prevent immigrants from finding jobs that match their qualifications is the inadequate transferability of their educational attainment in the host country (Brücker et al. 2021; Pecoraro and Wanner 2019). In our data, only 3.5% of Venezuelans with a college degree have had their credentials recognized in Peru. The prevalence of informality also plays a role in education being an imperfect proxy for overall skill level. This sector generally does not require high levels of qualifications, which makes over-education incidence more severe among informal workers (Chua and Chun 2016; Vivatsurakit and Vechbanyongratana 2021). In our case study, an informal job seems to be a desirable option for Venezuelans as a means to gain work schedule flexibility and avoid payroll taxes in formal employment (Blouin 2019; Blouin and Freier 2019; Cabrera et al. 2019).

Based on the lack of substitutability between natives and migrants presented in Table 2, we join the literature that uses alternative ways to define labor markets and adopt the skill cell approach using occupation groups.[22] In doing so, we create a more homogenous market, in which natives and immigrants are more substitutable. Lebow (2022a) documents high migrant-native substitutability along the occupation dimension and low substitutability across education groups for Venezuelan migrants in Colombia, supporting our analysis based on occupations. Table 3 reports the one-digit occupational distribution of native and immigrant workers.

[22]The inadequacy of the classic skill-cell approach in developed economies has already been documented (Sharpe and Bollinger 2020; Steinhardt 2011). These studies argue that an identification strategy based on formal education leads to biased results in labor markets characterized by a high relevance of formal qualifications combined with low rates of recognition of foreign qualifications, discrimination against migrants, and downgrading for immigrants upon arrival.

Table 3: Occupational Distribution of Natives and Venezuelan Immigrants in Peru, 2018

| | Peruvians | Venezuelans |
|---|---|---|
| Managers | 0.82 | 0.00 |
| Professionals | 10.10 | 1.22 |
| Technicians and Associate Professionals | 13.84 | 7.27 |
| Administrative Workers and Chiefs | 7.90 | 4.83 |
| Services and Sales Workers | 11.73 | 21.11 |
| Skilled Agricultural, Forestry, and Fishery Workers | 4.08 | 0.01 |
| Craft and Related Trades Workers | 9.42 | 15.39 |
| Plant and Machine Operators and Assemblers | 19.31 | 14.61 |
| Elementary Occupations | 22.80 | 35.56 |
| Observations | 4,007 | 3,789 |

Notes: Distributions for Peruvians and Venezuelans come from the last quarter of 2018 in ENAHO and ENPOVE, respectively. Samples come from the analysis of cells based on occupation groups.

The figures demonstrate huge disparities between Venezuelans and Peruvians in occupational distribution. While 10% of male Peruvians work in professional occupations, only 1% of the Venezuelan workers have a professional job. Immigrants tend to be highly represented in service and sales as well as elementary occupations, with 57% of Venezuelans working in these occupations, whereas 35% of Peruvians do so.

Table 3 presents a different sorting of migrants among occupations from that of empirical findings in migration studies in developed economies. Specifically, previous research for Germany, Spain, the U.K., and the U.S. show that immigrants are highly represented in jobs with manual tasks as opposed to service jobs that require interaction and communicative skills (Amuedo-Dorantes and de la Rica 2011; Manacorda et al. 2012; Peri and Sparber 2009; Steinhardt 2011). In our work, on the other hand, migrants and natives share the same language, which facilitates their job placement in occupations related to services.[23] The occupational distribution of migrants observed in Table 3 sheds light on the potential response of native workers to a supply shock. Venezuelans are concentrated in occupations in which informality is particularly high.[24] Thus, they directly compete with Peruvian workers in the informal

[23]The service group includes occupations such as waiters, waitresses, bartenders, cooks, housekeepers, hairdressers, barbers, beauticians, child-care workers, home-based personal care workers, transport conductors, and salespersons.

[24]Venezuelans are concentrated in elementary occupations, service and sales occupations, craft and trade work, and plant and machine operation and assembly (Table 3). Between 75% and 98%

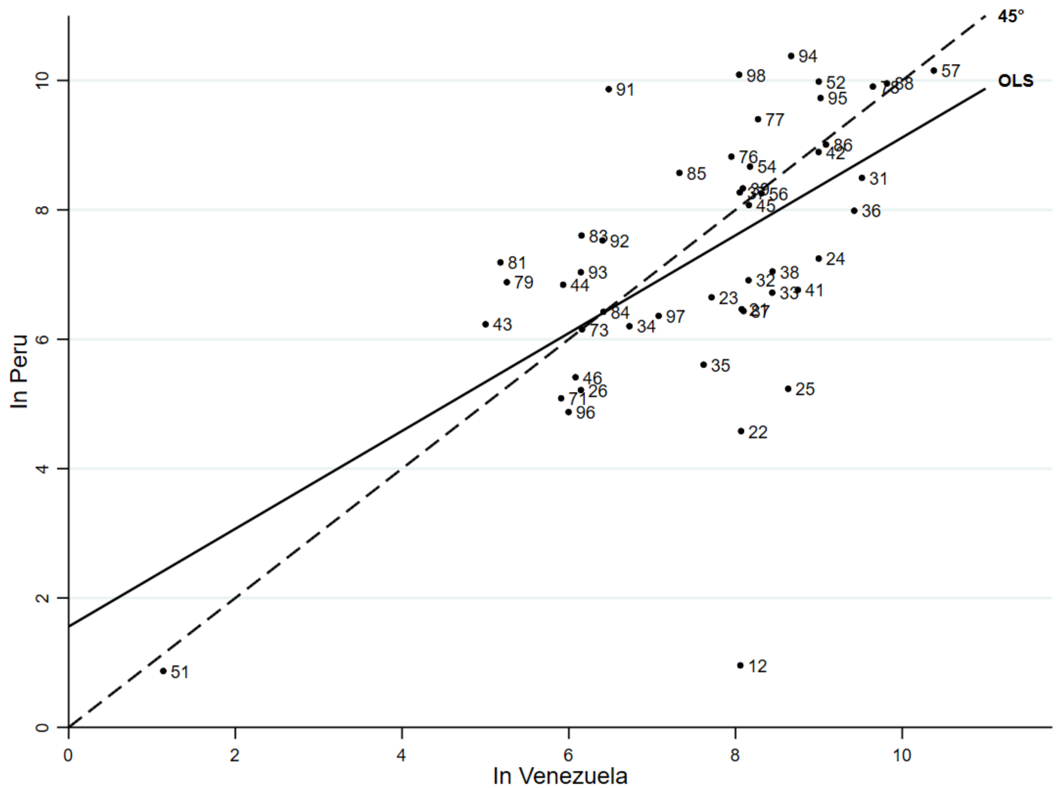
sector. This feature leads to expect a displacement of natives in the informal sector. However, the coexistence of formality and informality within firms and industries in the Peruvian labor market (Cisneros-Acevedo 2021; Galarza and Requejo 2019) suggests that migration could also displace formal workers employed at the margin.

As mentioned above, an important advantage of ENPOVE data is that they include the occupation migrants had in Venezuela prior to migration. This variable represents the exogenous source of variation for occupations in Peru in our analysis based on occupations.

Figure 3 shows the distribution of Venezuelan immigrants across occupations in Peru in 2018 and across occupations in Venezuela preceding immigration. Specifically, it graphs the log of the number of Venezuelans employed in an occupation in Peru in 2018, $ln(p)$, against the log of the number of Venezuelans formerly employed in the same occupation back in Venezuela, $ln(r)$, scaled to have the same total. Logs are displayed rather than absolute values because of the very large relative size of the largest occupations. The solid line on the graph plots the fitted values from an OLS regression of $ln(p)$ on $ln(r)$, which yields a coefficient of 0.95 (standard error .032). This coefficient evidences a very strong relation between immigrants' former and current occupations. Namely, for every 1% increase in the number of Venezuelans who worked in a particular occupation in Venezuela, the expected number of immigrants working in that same occupation in Peru increases by 0.95%, almost by the exact same magnitude.

of workers in these sectors are employed informally. This contrasts with informality shares in the remaining occupational groups (in which Venezuelans are rarely employed), with informality shares lower than 40% (ENAHO, last quarter of 2018).

Figure 3: Number of Migrants in each Occupation in Venezuela and Peru, 2018




If no Venezuelans switched occupations following migration, all points will lie along the 45-degree line. The points above the 45-degree line represent occupations to which Venezuelans disproportionally switched, whereas the points below the 45-degree line represent occupations from which Venezuelans disproportionally switched. Figure 3 shows that Venezuelans have mostly switched from medium or high-skilled occupations to low-skilled occupations.[25] That is, Peruvians in low-skilled occupa-

[25]ISCO-88 uses four skill levels to define the broad structure of the classification at the major group level (first digit occupation). These four skill levels are partly operationalized in terms of the International Standard Classification of Education (ISCED) and partly in terms of the job-related formal training which may be used to develop the skill level of persons who will carry out such jobs. Occupations with major group 9 are classified under the first skill level (primary education). Occupations with major groups 4-8 belong to the second skill level (secondary education plus on-the-job training). Occupations with major group 3 are classified under the third skill level (post-secondary education that leads to an award not equivalent to a university degree). Occupations with major group 2 belong to the fourth skill level (post-secondary education that leads to a university or postgraduate degree).

tions end up competing with more educated and experienced Venezuelans. This is in line with Table 2 which illustrates migrants are natives with similar education and experience are not comparable in the labor market, and supports our analysis based on occupations.

The most frequent former occupations of Venezuelans were salespersons, drivers and mobile plant operators, and metal, machinery, and related trades workers. These occupations also represent a high share among current occupations of Venezuelans in Peru (the corresponding points lie around the 45-degree line). On the other hand, the most frequent occupations of Venezuelans in Peru are street vendors, domestic helpers and cleaners, housekeeping and restaurant service workers, and salespersons. These occupations also represent a high share among former occupations for Venezuelans. Overall, the graph shows that the most representative former occupations of Venezuelans did not have the most outflows, and that the most representative current occupations of Venezuelans did not have the most inflows. This finding supports the use of Venezuelan's former occupations as an instrument.

# 5 Empirical Methodology

This study analyses the immigration effect at the national level using the skill-cell approach. The labor market is divided into skill groups where the membership of an individual in a skill group is defined with two different criteria: $(i)$ education and experience and $(ii)$ occupation. The subsequent empirical analysis is based on a reduced-form labor demand function that links the wages of native workers to the share of immigrants in their corresponding skill group.

## Education-Experience cells

Define a group of workers who have educational attainment $i$, labor market experience level $j$, and are observed in quarter $t$. The $(i, j, t)$ cell determines a skill group at time $t$. The impact of immigration on the wage level of skill groups is estimated by the following equation:

$$Y_{ijt} = \alpha + \theta p_{it} + s_i + x_j + \phi_t + (s_i \times x_j) + (s_i \times \phi_t) + (x_j \times \phi_t) + \sigma_{ijt}, \qquad (1)$$

where $Y_{ijt}$ denotes the average log monthly wage of natives with education $i$ and experience $j$ being observed at quarter $t$, and $p_{ijt}$ denotes the share of immigrant workers in the overall employed workforce in the education group $i$ and experience group $j$ at time $t$, making $\theta$ the coefficient of interest. The remaining controls are vectors of linear fixed effects for the education group ($s_i$), experience group ($x_j$), and quarter ($\phi_t$) to control for differences in average wages across education groups, experience groups, and over time. The interaction of education fixed effects with time ($s_i \times \phi_t$) and experience group fixed effects with time ($x_j \times \phi_t$) control for the changing impact of education or experience over time. Lastly, the interaction of education fixed effect and experience group fixed effect ($s_i \times x_j$) controls for any differences in the impact of experience on average wages across education groups. Thus, the impact of immigration on native wages is identified by variations in immigrant shares within education groups and experience groups over time.

Equation 1 is estimated via OLS. Regressions are weighted by the sample size used to calculate $Y_{ijt}$, and the standard errors are clustered by education-experience cells to adjust for possible serial correlation. The estimated coefficient of the immigrant share variable indicates the average percent change in wages corresponding to a 1 percentage point increase in new immigrants as a share of all workers.

## Occupation cells

We extend the analysis to the level of occupations based on the observation that in Peru, immigrants and natives work in different occupational segments despite having similar education and experience (Table 2). In this case, the use of the classical skill group approach based on formal education might lead to biased results, as already reported by Sharpe and Bollinger (2020) and Steinhardt (2011). By stratifying labor markets based on occupations, we make sure to match immigrants and natives who are most likely to compete in the same cell.

As noted earlier, since we only observe occupations of Venezuelans at a single point in time (last quarter of 2018), we follow Friedberg (2001) and adopt a first difference identification strategy by setting the first quarter of 2016 as our baseline period and the last quarter of 2018 as our endline. The impact of immigration on natives' labor market outcomes is estimated by regressing the change in the outcome variable in an occupation group on the inflow of employed immigrants in that group:

$$(Y_{o,t} - Y_{o,t-k}) = (\alpha_t - \alpha_{t-k}) + \theta(p_{o,t} - p_{o,t-k}) + (X_{o,t} - X_{o,t-k})'\phi + (\upsilon_{o,t} - \upsilon_{o,t-k}) \quad (2)$$

In Equation 2, $o$ denotes occupation, and $k$ is the number of quarters between the baseline and endline. The outcomes of interest are native wages, informal, formal, total employment, and hours worked in a typical week. Immigration occurs between 2016-I and 2018-IV so that $p_{o,t-k}$ equals zero and $p_{o,t}$ is the same as in a single cross-section specification. $X_{o,t}$ is a vector of control variables that captures the average age and average years of education of workers in occupation $o$ at time $t$, and $\upsilon_{o,t}$ is an error term. In the estimation of Equation 2, we weight observations with the sample size used to calculate the dependent variable. As the resulting number of observations is small, we use classic standard errors following Imbens and Kolesár (2016).

We run separate regressions for each outcome. All the dependent variables, as well as the immigration shock, are measured in logs. Specifically, $p_{o,t}$ is defined as the log number of employed Venezuelans in occupation $o$ at time $t$, and $Y_{o,t}$ is defined as the log number of Peruvians holding a job, a formal job, an informal job, the natives' average log number of hours worked and average log monthly wage in occupation $o$ at time $t$.[26] Thus, the estimated value of $\theta$ can be interpreted as an elasticity.

Slicing the labor market into occupations imposes the threat of endogeneity bias. $p_{o,t}$ may be positively correlated with the error term because both native and immigrant workers are drawn to occupations with good characteristics. The resulting endogeneity would lead to an underestimation of immigration's adverse employment impact. Alternatively, $p_{o,t}$ may be negatively correlated with the error term if Venezuelans can only find work in occupations with undesirable characteristics. To get around this bias, we use immigrants' former occupations in Venezuela as a source of exogenous variation for their occupations in Peru.

Immigrants will tend to seek work in their former occupations because their earnings will tend to be highest in the occupation in which they have the most training and experience. Therefore, we expect the labor supply shock to a certain occupation in Peru to be large (relative to the shock to other occupations) if the immigrant wave contained a large number of Venezuelans who held that occupation before migration. This source of variation is independent of the occupational wages in Peru since an immigrant's previous occupation in Venezuela was chosen based on labor market conditions in Venezuela and her individual preferences. Descriptive evidence of the relevance of this instrument is presented in Figure 3. Formal evidence is presented in

[26]Since the immigrant shock in 9 out of our 60 occupation cells takes the value of 0, we define its log transformation as follows: $p_{o,t} = log(1 + P_{o,t})$, where $P_{o,t}$ is the number of immigrants in occupation $o$ at time $t$ and can be equal to zero. For consistency, we apply the same transformation to natives' employment levels.

the next section.

Formally, the first stage for the specification in Equation 2 is:

$$(p_{o,t} - p_{0,t-k}) = \alpha(r_{o,t} - r_{o,t-k}) + \beta(x_{o,t} - x_{o,t-k})' + (\epsilon_{o,t} - \epsilon_{o,t-k}), \tag{3}$$

where $\epsilon_{o,t}$ represents an error term, $p_{o,t}$ and $x_{o,t}$ inherit their meaning from Equation 2, and $r_{ot}$ denotes the log number of Venezuelans who worked in occupation $o$ in Venezuela before migrating.[27]

# 6 Empirical Results

We first present the estimation results for the effect of immigration on natives' log monthly wages based on education-experience cells. We then present the results from estimations relying on cells defined by occupations.

## Education-Experience Cells

Table 4 reports the OLS estimates of the $\theta$ coefficient in Equation 1. Each row/column represents a different specification of Equation 1. The columns differ by the migrant variable specification. Column (1) reports the impact of a gender-specific shock on the log wages of natives. That is, male migrants compete with male natives. This specification addresses the issue that women have breaks in their employment histories but has the downside of potential measurement error in cells with small sample sizes.[28] Column (2) reports the impact of a migrant shock composed of both male and female migrants. While this specification has the advantage of increasing the cell sample size, it might misclassify women in experience groups.

Row 1 reports our preferred specification, where the regression is weighted by the number of observations used to calculate the average wage within a cell. We also present several robustness checks. Row 2 presents the same regression as in row 1, but unweighted. Row 3 presents estimates when we include the native labor force as an explanatory variable and row 4 redefines the measure of the immigrant shock $p_{ijt}$ to the (log) number of Venezuelan migrants.

[27]As with $p_{o,t-k}$, we set $r_{o,t-k} = 0$ following Friedberg (2001).

[28]A small sample size per skill cell tends to attenuate the impact of immigration because of sampling error in the measure of the immigrant supply shift (Aydemir and Borjas 2011).

Table 4: Effect of Immigration on Native Wages using Education and Experience Cells

| | (1) Gender-specific shock | (2) No gender-specific shock |
|---|---|---|
| 1. Weighted regression | -0.0115 | -0.0103 |
| | (0.0212) | (0.0195) |
| 2. Unweighted regression | -0.0054 | -0.0010 |
| | (0.0240) | (0.0213) |
| 3. Includes native labor force | -0.0101 | -0.0092 |
| | (0.0202) | (0.0189) |
| 4. Numerical immigration variable | -0.0084 | -0.0024 |
| | (0.0051) | (0.0062) |
| Observations | 384 | 384 |

Notes: Each row/column represents a unique specification. The sample in all specifications is employed men with 1–40 years of potential experience and positive wages, and the dependent variable is the mean of log native monthly wages in a given cell. All specifications include education, experience and quarter fixed effects, as well as their interactions. Row 1 presents the preferred estimates using the counts of native workers in each cell as weights. Row 2 presents unweighted estimates. Row 3 presents estimates from the weighted regression when native labor supply is included as a control variable. Row 4 presents estimates from the weighted regression when women are included in the migration variable. Cluster-robust standard errors are reported in parentheses. $^{***}$ p< .01, $^{**}$ p< .05, $^{*}$ p < .1.

We start by discussing our preferred estimates in row 1. The coefficient of -0.0115 in column (1) is not statistically significant at standard levels. The results, therefore, indicate that immigration has no adverse effect on the wages of natives. In column (2), we present the estimates when the migrant variable is composed of both male and female migrants. This coefficient remains negative and has a similar value to that presented in column (1), suggesting that measurement error due to small sample size or misclassification of women into experience cells is not an issue.

The remaining rows of Table 4 conduct a variety of specification tests to determine the sensitivity of the results. The coefficient in row 2, for example, indicates that the results are similar when the regressions are not weighted by the sample size of the skill group. In both columns, the coefficient remains negative, although smaller, and statistically not significant. In row 3, we include the native labor force as an explanatory variable. Since $p_{ijt}$ is the immigrant share of the overall employed workforce within a skill group, an increase in $p_{ijt}$ could occur from either an increase in immigrant labor supply or a decrease in native labor supply. As such, the estimates in row 3 report the impact of $p_{ijt}$ holding native labor supply constant. As before, the conclusion that migration does not have a detrimental wage impact is supported. However, since the change in the native labor force is likely endogenous, we do not prefer this specification, but we include it to be comparable to other literature and to demonstrate that our approach has similar qualitative effects across different specifications. Row 4 in Table 4 replicates the weighted analysis, replacing the ratio of Venezuelans in the overall employed workforce, $p_{ijt}$, with the log number of Venezuelans. This specification is qualitatively similar to the results using ratios.

Overall, Table 4 indicates that when we assume migrants and natives with the same education and experience compete in the labor market, migration does not adversely affect natives' wages. The lack of substitutability between natives and migrants presented in Table 2 could explain the null effects reported in Table 4. Therefore, we complement the analysis by estimating the wage impact of immigration based on occupation cells, as grouping immigrants and natives according to the occupations they hold guarantees that they are competing for a similar job position.

## Occupation Cells

We present the effects of changes in immigrant presence on changes in wages at the level of occupations in Table 5. As in the analysis based on education and experience, we present two specifications according to whether the migrant shock is gender-specific or not. Column (1) shows the results of a specification in which male migrants compete with male Peruvians. The specification in column (2), on the other hand, assumes that the migrant variable is composed of all Venezuelans, disregarding their gender. For every specification, we present OLS and 2SLS estimates, as well as the first-stage coefficient on the excluded instrument, $\hat{p}$, and the corresponding F-statistic. The first-stage F-statistic exceeds the threshold of 10 in both specifications. Recall that, for this analysis, the immigration variable is measured as the (log) number of Venezuelans. Thus, the immigration variable is the same as in row 4 of Table 4.

Table 5: The Effects of Immigration on Native Wages Using Occupation Cells

| | (1) Gender-specific shock | (2) No gender-specific shock |
|---|---|---|
| OLS | 0.0026 | 0.0037 |
| | (0.0077) | (0.0078) |
| IV | -0.0139 | -0.0130 |
| | (0.0130) | (0.0129) |
| First stage estimates | 1.0499*** | 1.0203*** |
| | (0.1882) | (0.1773) |
| F-statistic | 31.13 | 33.13 |
| Observations | 60 | 60 |

Notes: The sample is employed men with 1-40 years of potential experience and positive wages. The dependent variable is the change in the mean of log monthly wages in a given cell and the independent variable is the log number of male immigrants in that cell. In the 2SLS regressions, the number of immigrants in an occupation is instrumented with the former number of immigrants working in that occupation before migration. The specifications control for the average age and years of education of natives. Observations are weighted by the number of male natives used to compute the dependent variable. Standard errors are reported in parenthesis. $^{***}$ p< .01, $^{**}$ p< .05, $^{*}$ p < .1.

According to column (1), an increase in employment due to an inflow of immigrants is associated with a small increase in native wages. However, we cannot reject the hypothesis that immigration has no impact on native wages with our conservative standard errors.[29] When the immigration shock is composed of both male and female migrants (column 2), the coefficient is qualitatively similar. After the endogenous selection is accounted for in the 2SLS model, the immigration coefficient becomes negative and remains statistically not significant.

The contrast between the OLS and IV estimates indicates that the distribution of Venezuelan immigrants across occupations in Peru is not independent of the unobserved determinants of wages in those occupations and that, as a result, OLS underestimates the immigration's negative impact on native wages. The positive bias to OLS uncovered in this study is in line with previous literature for developed (Orrenius and Zavodny 2007; Sharpe and Bollinger 2020) and developing economies

[29]Our claim of statistical significance prevails once we consider heteroskedasticity-robust standard errors. Moreover, the corresponding Kleibergen-Paap test statistic also exceeds the threshold of 10 in both specifications of the migrant shock.

(Broussard 2017; Del Carpio and Wagner 2016), including that for hosting countries of Venezuelan migrants (Caruso et al. 2021; Lebow 2022b).

Our results also align with studies supporting the use of alternative criteria to define labor markets in the skill-cell approach. Steinhardt (2011) for Germany and Sharpe and Bollinger (2020) for the United States show that when workers are grouped based on occupations, the estimated impact of immigration is larger. Our coefficients in the occupation analysis (Table 5) are also larger than those in the education-experience analysis (row 4 in Table 4), although they remain statistically not significant.

In light of the previous literature that explained the null effect of immigration on the wages of natives with the lack of substitutability between immigrants and natives, our finding is unexpected. The cultural proximity between Venezuelans and Peruvians, as well as our empirical approach based on the grounds that occupational groups are categories where the degree of substitution between natives and immigrants is bound to be much better gauged, initially suggested that immigration would be detrimental to natives. Moreover, our analysis covers a period of 2 years after the immigrant flows started; thus, the estimated wage effects can be regarded as "short-term" estimates. This time frame lowers the chances of a reaction of capital to an immigration inflow, which reinforces the expectation of downward pressure on wages. Therefore, our finding that immigration does not negatively affect the wages of natives leads us to consider different ways of adjustments of the local labor market.

We, therefore investigate whether the employment of natives at the extensive and intensive margins responds to immigration. Table 6 presents OLS and IV estimates of the impact of a gender-specific migration shock on Peruvians' employment and hours of work. We present the results for overall, formal, and informal employment. As in the previous regressions, observations are weighted by the sample size used to calculate the dependent variable.

Table 6: The Effects of Immigration on Native Employment Using Occupation Cells

| | Formal Sector | | Informal Sector | | Overall | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Employment | Hours worked | Employment | Hours worked | Employment | Hours worked |
| OLS | -0.0485 | -0.0074 | -0.0228 | 0.0135** | -0.0141 | 0.0070 |
| | (0.0403) | (0.0082) | (0.0236) | (0.0066) | (0.0164) | (0.0051) |
| IV | -0.1547** | 0.0218 | -0.0240 | 0.0237** | -0.0273 | 0.0182** |
| | (0.0706) | (0.0154) | (0.0371) | (0.0106) | (0.0267) | (0.0086) |
| First stage estimates | 0.8900*** | 0.8741*** | 1.1369*** | 1.1376*** | 1.0499*** | 1.0499*** |
| | (0.1694) | (0.1772) | (0.2033) | (0.2075) | (0.1882) | (0.1882) |
| F-statistic | 27.59 | 24.34 | 31.26 | 30.07 | 31.13 | 31.13 |
| Observations | 57 | 53 | 56 | 54 | 60 | 60 |

Notes: The sample is employed men with 1-40 years of potential experience and positive wages (columns 5,6) and is further restricted to sector-specific employment in columns 1-4. Individuals with 0 hours of work are dropped from the sample only in the regressions of hours of work. The dependent variable is the change in the log number of employed natives (columns 1, 3, 5) or in the weekly hours worked in the main job (columns 2, 4, 6) in a given occupation. The independent variable is the log number of male immigrants working in a given occupation. In the 2SLS regressions, the number of immigrants in an occupation is instrumented with the former number of immigrants working in that occupation before migration. The specifications control for the average age and years of education of natives. Observations are weighted by the number of male natives used to compute the dependent variable. Standard errors are reported in parenthesis.$^{***}$ p< .01, $^{**}$ p< .05, $^{*}$ p < .1.

Column (1) of Table 6 shows that migration negatively affects labor formality at the extensive margin. The point estimates indicate that for every 10% increase in the number of employed Venezuelans, native formal employment falls by about 1.5%. There is a null effect on informal employment, suggesting that displaced native workers in the formal sector either leave entirely the workforce or join the unemployed (column 3). The prevalence of informal employment in the Peruvian labor market results in a null effect of immigration on overall employment at the extensive margin (column 5).

On the intensive margin, those native workers who continue to participate in the labor market increase little to nothing the time spent working in a given week. Specifically, for every 10% increase in the number of employed Venezuelans, the time spent working increases by 0.2% (column 6). The reported effect on hours of work is much smaller than that on formal employment, indicating that natives working in occupations that employed more immigrants barely increase the time spent working, relative to natives working in occupations that employed fewer immigrants. The estimated effect on hours of work for informal workers is larger but still negligible. The prevalence of part-time work among informal workers could explain this difference in magnitude.

In Table 6, formal and informal employment regressions use different weights than the overall employment regression. In Appendix Table A2, we show the estimates when all employment regressions are weighted by the number of male natives with positive wages. The results presented so far prevail. However, the effect of immigration on hours worked by informal workers becomes not significant. Considering the small magnitude of this coefficient and its loss of significance when using the sample size of the employed natives as weights, we do not argue the small effect on hours of work is driven by informal employment.

Thus, natives were displaced from high-valued occupations (i.e., formal jobs). There is no indication that such displacements resulted in shifts from high-valued to low-valued occupations (i.e., informal jobs) as average native wages do not decline. Moreover, the little to no effect on hours of employment is consistent with the null effect on wages. There is no need to compensate lower earnings with more hours of work because wages remain unchanged.

## Robustness checks

In this section, we address concerns that our estimates may be biased due to abnormal labor market behavior in the baseline, cyclical patterns in the native labor market, the adopted measure of the immigrant shock as well as patterns in the allocation of the immigration shock to occupational groups. We first change the baseline period to the first quarter of 2015. The results are displayed in Table 7.

Table 7: The Effects of Immigration on Native Employment Using Occupation Cells, with Change in Baseline Year

| | Formal Sector | | Informal Sector | | Overall | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Employment | Hours worked | Employment | Hours worked | Employment | Hours worked |
| OLS | -0.0871 | 0.0014 | -0.0091 | 0.0105 | -0.0082 | 0.0072 |
| | (0.0525) | (0.0097) | (0.0156) | (0.0066) | (0.0144) | (0.0052) |
| IV | -0.3307*** | 0.0161 | -0.0101 | 0.0034 | -0.0312 | 0.0033 |
| | (0.1017) | (0.0165) | (0.0254) | (0.0109) | (0.0243) | (0.0087) |
| First stage estimates | 0.8615*** | 0.9119*** | 1.0692*** | 1.0692*** | 0.9945*** | 0.9945*** |
| | (0.1627) | (0.1866) | (0.2037) | (0.2037) | (0.1866) | (0.1866) |
| F-statistic | 28.05 | 23.87 | 27.57 | 27.57 | 28.40 | 28.40 |
| Observations | 56 | 51 | 55 | 55 | 59 | 59 |

Notes: Estimates come from changing the baseline period to the first quarter of 2015. The sample is employed men with 1-40 years of potential experience and positive wages (columns 5,6) and is further restricted to sector-specific employment in columns 1-4. Individuals with 0 hours of work are dropped from the sample only in the regressions of hours of work. The dependent variable is the change in the log number of employed natives (columns 1, 3, 5) or in the weekly hours worked in the main job (columns 2, 4, 6) in a given occupation. The independent variable is the log number of male immigrants working in a given occupation. In the 2SLS regressions, the number of immigrants in an occupation is instrumented with the former number of immigrants working in that occupation before migration. The specifications control for the average age and years of education of natives. Observations are weighted by the number of male natives used to compute the dependent variable. Standard errors are reported in parenthesis.$^{***}$ p< .01, $^{**}$ p< .05, $^{*}$ p < .1.

The results are qualitatively identical and slightly larger in absolute value. This allows us to rule out that our main results are driven by abnormal labor market behavior in the original baseline period.

A valid concern is whether our results are driven by a cyclical pattern in the business cycle that more or less repeats itself each year due to exogenous factors such as the weather or regular calendar events. For instance, if industrial production drops in the first quarter of the year but increases significantly in the last quarter of the year, our results can just reflect a temporal imbalance of employment between an off-season and a peak season. Table 8 presents the immigration effects when changing the baseline period to the first quarter of 2016 to the fourth quarter of the same year.

Table 8: The Effects of Immigration on Native Employment Using Occupation Cells, with Change in the Baseline Quarter

| | Formal Sector | | Informal Sector | | Overall | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Employment | Hours worked | Employment | Hours worked | Employment | Hours worked |
| OLS | -0.0641* | -0.0018 | 0.0212 | 0.0147* | 0.0147 | 0.0119** |
| | (0.0370) | (0.0076) | (0.0197) | (0.0075) | (0.0135) | (0.0058) |
| IV | -0.1280** | -0.0052 | 0.0296 | 0.0171 | 0.0249 | 0.0106 |
| | (0.0616) | (0.0125) | (0.0308) | (0.0117) | (0.0217) | (0.0093) |
| First stage estimates | 0.8795*** | 0.8898*** | 1.1266*** | 1.1253*** | 1.0391*** | 1.0391*** |
| | (0.1629) | (0.1747) | (0.2010) | (0.2056) | (0.1845) | (0.1845) |
| F-statistic | 29.14 | 25.93 | 31.42 | 29.96 | 31.72 | 31.72 |
| Observations | 57 | 54 | 55 | 53 | 59 | 59 |

Notes: Estimates come from changing the baseline period to the fourth quarter of 2016. The sample is employed men with 1-40 years of potential experience and positive wages (columns 5,6) and is further restricted to sector-specific employment in columns 1-4. Individuals with 0 hours of work are dropped from the sample only in the regressions of hours of work. The dependent variable is the change in the log number of employed natives (columns 1, 3, 5) or in the weekly hours worked in the main job (columns 2, 4, 6) in a given occupation. The independent variable is the log number of male immigrants working in a given occupation. In the 2SLS regressions, the number of immigrants in an occupation is instrumented with the former number of immigrants working in that occupation before migration. The specifications control for the average age and years of education of natives. Observations are weighted by the number of male natives used to compute the dependent variable. Standard errors are reported in parenthesis.*** p< .01, ** p< .05, * p < .1.

Table 8 indicates that, when using the same quarter in the baseline and endline, the immigration employment effects are equivalent to our main results (see Table 6). Changing the baseline quarter only slightly lowers the magnitude of the effect of immigration on formal employment from 0.33 to 0.13. Thus, we confirm that immigration, rather than seasonality, is the main driver of our results.

Final checks are performed to gauge the extent to which our estimates are influenced by the adopted measure of the immigrant shock or by spurious labor markets. For the first matter, we apply the inverse hyperbolic sine transformation to the immigrant shock and the employment outcomes.[30] The results are displayed in Appendix Table A3. Our results hold their qualitative nature and are almost identical in magnitude. For the second matter, we perform several placebo experiments in which we randomly assign the migrant shock to arbitrary native occupations. None of the placebo experiments, reported in Appendix Table A4, replicate our main findings. These results indicate that our findings are likely to be reflecting a true causal relationship and not a spurious correlation.

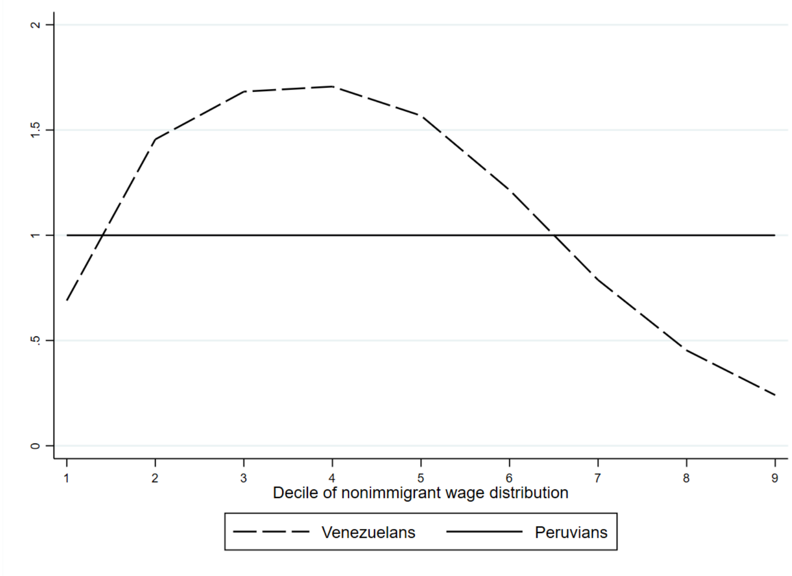
[30] For a random variable $x$, this is defined as $log(x + \sqrt{x+1})$.

# 7 Economic Interpretation and Discussion

There are several channels through which the influx of immigrants may affect the labor market outcomes of natives. First, workers may adjust their supply of labor in response to immigration. In particular, they may increase the number of hours worked to compensate for their lower earnings potential. Second, there could be a shift in the composition of labor favoring low-skilled occupations. If skills are substitutable for some occupations, then employers might substitute highly skilled natives for low-skilled migrant workers. Similarly, skilled natives might remain employed but shift from high-valued to low-valued occupations. In either case, the result would be a wage decline, as seems to have happened in Colombia (Caruso et al. 2021). Finally, the shift in the composition could be the other way around. Native workers shift from informal to formal employment, resulting in an occupational upgrading for natives (Broussard 2017; Del Carpio and Wagner 2016). This is a result of natives taking advantage of the low-cost informal workers and creating jobs.

Our robust null effect on wages rules out any shift in the composition of employment. Instead, we find that immigration affects natives' labor supply at the extensive margin of formal employment without affecting informal employment. An important question is what happens with those who lost their jobs: did they leave the workforce entirely or join the unemployed? We are unable to test any adjustment mechanisms because our analysis based on occupations is based on the employed workforce. However, knowing who competes with whom in the labor market can shed light on the underlying mechanism. Figure 4 depicts kernel estimates of the observed density of immigrants in the non-immigrant wage distribution. The horizontal line shows as a reference the native wage distribution. The kernel estimates are above the horizontal line at wages where immigrants are more concentrated than natives, and below the horizontal line at wages where immigrants are less concentrated than natives.

Figure 4: Position of Venezuelan Immigrants in the Native Wage Distribution, 2018




*Note:* Shown are kernel estimates of the observed density of immigrants in the native wage distribution. The sample is employed men with 1-40 years of potential experience and positive wages. Individuals with 0 hours of work are dropped from the sample.

Figure 4 illustrates that Venezuelans are overrepresented at the bottom half of the native wage distribution and underrepresented in the upper end of the wage distribution. Thus, those groups with the lowest propensity to be employed formally should be most affected by the inflow of Venezuelan migrants.

Evidence in Figure 4 added to the fact that formal and informal workers combine to produce output in the Peruvian labor market suggests that Peruvians employed formally are substituted by low-cost informal immigrant labor. That is, immigrants lower the cost of production, and employers substitute natives with less expensive immigrant labor.[31] Our findings are in line with recent Peruvian evidence indicating that migration had no detrimental effect on wages (Boruchowicz et al. 2021; Groeger et al. 2022) and with Delgado-Prieto (2022) and Lebow (2022b) regarding job displacements in the formal sector that seem to be driven by the substitution of informal migrant labor for formal native labor. Further research is needed to test whether migration rises formal employment in the long run.

[31] See Céspedes Reynaga and Ramírez-Rondán (2021), Cisneros-Acevedo (2021), and Galarza and Requejo (2019) for evidence of how informal and formal labor combine in production in the Peruvian labor market.

## 8 Conclusions

This paper combines data on the Venezuelan population residing in Peru in 2018 and the Peruvian Household Employment Survey (2016-2018) to assess the impact of Venezuelan migration on Peruvian labor market conditions.

The most important task in examining the causal impact of immigration on native labor market outcomes is identifying who competes with whom. The prior literature has relied upon education and experience groups to estimate the effect of immigration on native wages. We argue that because immigrants and natives are likely to work in different occupational segments despite having similar education and work experience, this grouping may not be ideal. We improve upon the methodology by forming skill groups using occupation groups.

Because occupational choice is endogenous, we rely on Venezuelans' former occupations as a source of exogenous variation. Our 2SLS estimates indicate a null effect on native wages. We then turn to uncover the impact of immigration on native employment. We find that the recent immigration of Venezuelans has affected formal native employment at the extensive margin. For every 10% increase in the number of employed Venezuelans, native formal employment falls by about 1.5%. There is a null effect on informal employment, suggesting that displaced native workers in the formal sector either leave entirely the workforce or join the unemployed. Importantly, our results are robust to changes in the baseline period, to different transformations of the dependent and independent variables, and cannot be replicated by placebo experiments.

Our results align with informal migrant work and formal native labor being substitutes in production revealed in previous literature (Delgado-Prieto 2022; Lebow 2022b). Furthermore, migrants are concentrated at the bottom half of the native wage distribution, suggesting that natives employed in the least valued occupations are those being substituted with immigrant informal labor.

## References

Aksu, Ege, Refik Erzan, and Murat Güray Kırdar. "The impact of mass migration of Syrians on the Turkish labor market". In: *Labour Economics* 76 (2022), p. 102183. ISSN: 0927-5371. DOI: https://doi.org/10.1016/j.labeco.

2022.102183. URL: https://www.sciencedirect.com/science/article/pii/S0927537122000744.

Altonji, Joseph G. and David Card. "The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives". In: *Immigration, Trade, and the Labor Market*. University of Chicago Press, 1991, pp. 201–234. URL: http://www.nber.org/chapters/c11773.

Amuedo-Dorantes, Catalina and Sara de la Rica. "Complements or substitutes? Task specialization by gender and nativity in Spain". In: *Labour Economics* 18.5 (2011), pp. 697–707. ISSN: 0927-5371. DOI: https://doi.org/10.1016/j.labeco.2011.02.002. URL: https://www.sciencedirect.com/science/article/pii/S0927537111000297.

Asencios, Roger and Renzo Castellares. *The Impact of Venezuelan Immigration on Employment and Wages: the Peruvian Case*. Documentos de Trabajo 2020-002. 2020. URL: https://www.bcrp.gob.pe/docs/Publicaciones/Documentos-de-Trabajo/2020/documento-de-trabajo-002-2020.pdf.

Aydemir, Abdurrahman and George J. Borjas. "Attenuation Bias in Measuring the Wage Impact of Immigration". In: *Journal of Labor Economics* 29.1 (Jan. 2011), pp. 69–112. DOI: 10.1086/656360. URL: https://doi.org/10.1086%2F656360.

Blouin, Cécile. *Estudio sobre el perfil socio económico de la población venezolana y sus comunidades de acogida: una mirada hacia la inclusión*. Tech. rep. Instituto de Democracia y Derechos Humanos de la Pontificia Universidad Católica del Perú y PADF, 2019. URL: http://repositorio.pucp.edu.pe/index/handle/123456789/166504.

Blouin, Cécile and Luisa Feline Freier. "Población venezolana en Lima: entre la regularización y la precariedad." In: *Crisis y migración de población venezolana. Entre la desprotección y la seguridad jurídica en Latinoamerica*. Ed. by Fernando Lozano Ascensio Luciana Gandini and Victoria Prieto. Universidad Nacional Autónoma de México, 2019, pp. 157–184. URL: https://www.sdi.unam.mx/docs/libros/SUDIMER-CyMdPV.pdf.

Böhme, Marcus H. and Sarah Kups. *The economic effects of labour immigration in developing countries*. Working Paper 335. OECD Development Centre, 2017. URL: https://doi.org/10.1787/c3cbdd52-en.

Bonilla-Mejía, Leonardo, Leonardo Fabio Morales, Didier Hermida-Giraldo, and Luz A Flórez. *The Labor Market of Immigrants and Non-Immigrants Evidence from the*

*Venezuelan Refugee Crisis*. Borradores de Economía 1119. Banco de la República, 2020. DOI: 10.32468/be.1119. URL: https://doi.org/10.32468/be.1119.

Borjas, George J. "Immigrants, minorities, and labor market competition". In: *ILR Review* 40.3 (1987), pp. 382–392. URL: https://doi.org/10.1177%2F001979398704000305.

Borjas, George J. "The economics of immigration". In: *Journal of economic literature* 32.4 (1994), pp. 1667–1717. URL: https://www.jstor.org/stable/2728791.

Borjas, George J. "The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market*". In: *The Quarterly Journal of Economics* 118.4 (Nov. 2003), pp. 1335–1374. ISSN: 0033-5533. DOI: 10.1162/003355303322552810. eprint: https://academic.oup.com/qje/article-pdf/118/4/1335/5427319/118-4-1335.pdf. URL: https://doi.org/10.1162/003355303322552810.

Borjas, George J., Richard B. Freeman, and Lawrence F. Katz. *On the Labor Market Effects of Immigration and Trade*. Working Paper Series 3761. National Bureau of Economic Research, 1992. DOI: 10.3386/w3761.

Borjas, George J., Richard B Freeman, and Lawrence F Katz. *Searching for the Effect of Immigration on the Labor Market*. Working Paper 5454. National Bureau of Economic Research, 1996. DOI: 10.3386/w5454. URL: https://doi.org/10.3386/w5454.

Boruchowicz, Cynthia, Cesar Martinelli, and Susan W Parker. "Economic Consequences of Mass Migration: The Venezuelan Exodus in Peru". 2021. DOI: 10.2139/ssrn.3847897.

Breunig, Robert, Nathan Deutscher, and Hang Thi To. "The relationship between immigration to Australia and the labour market outcomes of Australian-born workers". In: *Economic Record* 93.301 (2017), pp. 255–276. URL: https://doi.org/10.1111/1475-4932.12328.

Broussard, Nzinga H. "Immigration and the Labor Market Outcomes of Natives in Developing Countries: A Case Study of South Africa". In: *Economic Development and Cultural Change* 65.3 (Apr. 2017), pp. 389–424. DOI: 10.1086/690648. URL: https://doi.org/10.1086%2F690648.

Brücker, Herbert, Albrecht Glitz, Adrian Lerche, and Agnese Romiti. "Occupational Recognition and Immigrant Labor Market Outcomes". In: *Journal of Labor Economics* 39.2 (Apr. 2021), pp. 497–525. DOI: 10.1086/710702. URL: https://doi.org/10.1086%2F710702.

Cabrera, Donna C., Gabriela M. Cano, and Alexandra Castro. "Procesos recientes de movilidad humana entre Venezuela y Colombia 2016-2018". In: *Crisis y migración de población venezolana. Entre la desprotección y la seguridad jurídica en Latinoamerica*. Ed. by Fernando Lozano Ascensio Luciana Gandini and Victoria Prieto. Universidad Nacional Autónoma de México, 2019, pp. 59–94. URL: https://www.sdi.unam.mx/docs/libros/SUDIMER-CyMdPV.pdf.

Card, David. "The impact of the Mariel boatlift on the Miami labor market". In: *ILR Review* 43.2 (1990), pp. 245–257. URL: https://doi.org/10.1177%2F001979399004300205.

— "Immigration and Inequality". In: *American Economic Review* 99.2 (May 2009), pp. 1–21. DOI: 10.1257/aer.99.2.1.

Carrasco, Raquel, Juan F Jimeno, and A Carolina Ortega. "The effect of immigration on the labor market performance of native-born workers: some evidence for Spain". In: *Journal of Population Economics* 21.3 (2008), pp. 627–648. URL: https://doi.org/10.1007/s00148-006-0112-9.

Caruso, German, Christian Gomez Canon, and Valerie Mueller. "Spillover effects of the Venezuelan crisis: migration impacts in Colombia". In: *Oxford Economic Papers* 73.2 (Nov. 2021), pp. 771–795. ISSN: 0030-7653. DOI: 10.1093/oep/gpz072. eprint: https://academic.oup.com/oep/article-pdf/73/2/771/37137605/gpz072.pdf. URL: https://doi.org/10.1093/oep/gpz072.

Ceritoglu, Evren, H. Burcu Gurcihan Yunculer, Huzeyfe Torun, and Semih Tumen. "The impact of Syrian refugees on natives'labor market outcomes in Turkey: evidence from a quasi-experimental design". In: *IZA Journal of Labor Policy* 6.5 (2017). DOI: 10.1186/s40173-017-0082-4. URL: https://doi.org/10.1186/s40173-017-0082-4.

Céspedes Reynaga, Nikita and Nelson R. Ramírez-Rondán. "Job Finding and Separation Rates in an Economy with High Labor Informality". In: *Workplace Productivity and Management Practices*. Ed. by Solomon W. Polachek, Konstantinos Tatsiramos, Giovanni Russo, and Gijs van Houten. Vol. 49. Emerald Publishing Limited, 2021, pp. 277–302. ISBN: 978-1-80117-675-0, 978-1-80117-674-3. DOI: 10.1108/S0147-912120210000049010. URL: https://doi.org/10.1108/S0147-912120210000049010.

Chua, Kenn and Natalie Chun. *In search of a better match: Qualification mismatches in developing Asia*. Economics Working Paper Series 476. Asian Development Bank, 2016. DOI: 10.2139/ssrn.2811502.

Cisneros-Acevedo, Camila. “Unfolding Trade Effect in Two Margins of Informality. The Peruvian Case”. In: *The World Bank Economic Review* 36.1 (Oct. 2021), pp. 141–170. ISSN: 0258-6770. DOI: 10.1093/wber/lhab023.

Cohen-Goldner, Sarit and M Daniele Paserman. “The dynamic impact of immigration on natives’ labor market outcomes: Evidence from Israel”. In: *European Economic Review* 55.8 (2011), pp. 1027–1045. DOI: 10.1016/j.euroecorev.2011.05.002.

Del Carpio, Ximena V and Mathis Wagner. *The Impact of Syrian Refugees on the Turkish Labor Market*. Policy Research Working Paper 7402. World Bank, 2016. URL: https://ssrn.com/abstract=2650218.

Delgado-Prieto, Lukas. *Immigration, Wages, and Employment under Informal Labor Markets*. Working Paper. Economics 2022-12. Universidad Carlos III de Madrid, 2022. URL: http://hdl.handle.net/10016/35664.

Departamento Administrativo Nacional de Estadística. *Medición de empleo informal y seguridad social - Trimestre móvil noviembre 2018 - enero 2019*. Boletín Técnico. 2019. URL: https://www.dane.gov.co/files/investigaciones/boletines/ech/ech_informalidad/bol_geih_informalidad_dic21_feb22.pdf.

Duncan, Otis Dudley and Beverly Duncan. “Residential distribution and occupational stratification”. In: *American journal of sociology* 60.5 (1955), pp. 493–503. DOI: 10.1086/221609.

Dustmann, Christian, Tommaso Frattini, and Ian P. Preston. “The Effect of Immigration along the Distribution of Wages”. In: *The Review of Economic Studies* 80.1 (Apr. 2012), pp. 145–173. ISSN: 0034-6527. DOI: 10.1093/restud/rds019.

Dustmann, Christian and Ian Preston. “Comment: Estimating the effect of immigration on wages”. In: *Journal of the European Economic Association* 10.1 (2012), pp. 216–223. URL: https://doi.org/10.1111/j.1542-4774.2011.01056.x.

Friedberg, Rachel M. “The impact of mass migration on the Israeli labor market”. In: *The Quarterly Journal of Economics* 116.4 (2001), pp. 1373–1408. URL: https://doi.org/10.1162/003355301753265606.

Galarza, Francisco and Fernando Requejo. *Reducing Informality Using Two-Sided Incentives: Theory and Experiment*. Working Paper 149. Peruvian Economic Association, 2019. URL: https://sistemas.colmex.mx/Reportes/LACEALAMES/LACEA-LAMES2019_paper_305.pdf.

Goldin, Claudia. “The Political Economy of Immigration Restriction in the United States, 1890 to 1921”. In: *The Regulated Economy: A Historical Approach to Po-

*litical Economy*. University of Chicago Press, 1994, pp. 223–258. URL: http://www.nber.org/chapters/c6577.

Groeger, Andre, Gianmarco León-Ciliotta, and Steven Stillman. *Immigration, Labor Markets and Discrimination*. Policy Research Working Paper 9982. World Bank, 2022. URL: http://hdl.handle.net/10986/37206.

Grossman, Jean Baldwin. "The substitutability of natives and immigrants in production". In: *The review of economics and statistics* 64.4 (1982), pp. 596–603. URL: https://doi.org/10.2307/1923944.

Imbens, Guido W. and Michal Kolesár. "Robust Standard Errors in Small Samples: Some Practical Advice". In: *The Review of Economics and Statistics* 98.4 (Oct. 2016), pp. 701–712. ISSN: 0034-6535. DOI: 10.1162/REST_a_00552. eprint: https://direct.mit.edu/rest/article-pdf/98/4/701/1918261/rest_a_00552.pdf. URL: https://doi.org/10.1162/REST_a_00552.

INEI. *Condiciones de vida de la poblacion venezolana que reside en Perú*. Tech. rep. Instituto Nacional de Estadísticas e Informática, 2019. URL: https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1666/libro.pdf.

Kossoudji, Sherrie A and Deborah A Cobb-Clark. "Coming out of the shadows: Learning about legal status and wages from the legalized population". In: *Journal of Labor Economics* 20.3 (2002), pp. 598–628. URL: https://doi.org/10.1086/339611.

LaLonde, Robert J. and Robert H. Topel. "Labor Market Adjustments to Increased Immigration". In: *Immigration, Trade, and the Labor Market*. Ed. by John M. Abowd and Richard B. Freeman. University of Chicago Press, 1991, pp. 167–200. URL: http://www.nber.org/chapters/c11772.

Lebow, Jeremy. "Immigration and Occupational Downgrading in Colombia". Unpublished manuscript. 2022. URL: https://static1.squarespace.com/static/6064ff1093aaa5277d9d8df9/t/630f84afdeaaa651984e623b/1661961395881/lebow2021.pdf.

— "The labor market effects of Venezuelan migration to Colombia: reconciling conflicting results". In: *IZA Journal of Development and Migration* 13.1 (2022). DOI: 10.2478/izajodm-2022-0005. URL: https://doi.org/10.2478/izajodm-2022-0005.

Manacorda, Marco, Alan Manning, and Jonathan Wadsworth. "The impact of immigration on the structure of wages: theory and evidence from Britain". In: *Jour-*

*nal of the European economic association* 10.1 (2012), pp. 120–151. URL: https://doi.org/10.1111/j.1542-4774.2011.01049.x.

Morales, Fernando and Martha Denisse Pierola. *Venezuelan Migration in Peru: Short-term Adjustments in the Labor Market*. Working Paper 1146. Inter-American Development Bank, Aug. 2020. DOI: 10.18235/0002594. URL: https://doi.org/10.18235%2F0002594.

Olivieri, Sergio, Francesc Ortega, Ana Rivadeneira, and Eliana Carranza. "The Labour Market Effects of Venezuelan Migration in Ecuador". In: *The Journal of Development Studies* 58.4 (2022), pp. 713–729. DOI: 10.1080/00220388.2021.1988077. eprint: https://doi.org/10.1080/00220388.2021.1988077. URL: https://doi.org/10.1080/00220388.2021.1988077.

Orrenius, Pia M and Madeline Zavodny. "Does immigration affect wages? A look at occupation-level evidence". In: *Labour Economics* 14.5 (2007), pp. 757–773. DOI: 10.1016/j.labeco.2006.09.006. URL: https://doi.org/10.1016/j.labeco.2006.09.006.

Ottaviano, Gianmarco IP and Giovanni Peri. "Rethinking the effect of immigration on wages". In: *Journal of the European economic association* 10.1 (2012), pp. 152–197. URL: https://doi.org/10.1111/j.1542-4774.2011.01052.x.

Pecoraro, Marco and Philippe Wanner. "Does the Recognition of Foreign Credentials Decrease the Risk for Immigrants of Being Mismatched in Education or Skills?" In: *Migrants and Expats: The Swiss Migration and Mobility Nexus*. Ed. by Ilka Steiner and Philippe Wanner. Cham: Springer International Publishing, 2019, pp. 161–186. ISBN: 978-3-030-05671-1. URL: https://doi.org/10.1007/978-3-030-05671-1_7.

Peñaloza-Pacheco, Leonardo. "Living with the neighbors: the effect of Venezuelan forced migration on the labor market in Colombia". In: *Journal for Labour Market Research* 56.14 (2022). DOI: 10.1186/s12651-022-00318-3. URL: https://doi.org/10.1186/s12651-022-00318-3.

Peri, Giovanni and Chad Sparber. "Task Specialization, Immigration, and Wages". In: *American Economic Journal: Applied Economics* 1.3 (2009), pp. 135–169. DOI: 10.1257/app.1.3.135.

Schoeni, Robert F. *The Effect of Immigrants on the Employment and Wages of Native Workers: Evidence from the 1970s and 1980s*. Santa Monica, CA: RAND Corporation, 1997. URL: https://www.rand.org/pubs/drafts/DRU1408.html.

Sharpe, Jamie and Christopher R. Bollinger. "Who competes with whom? Using occupation characteristics to estimate the impact of immigration on native wages". In: *Labour Economics* 66 (2020), p. 101902. ISSN: 0927-5371. URL: https://doi.org/10.1016/j.labeco.2020.101902.

Steinhardt, Max Friedrich. "The wage impact of immigration in germany-new evidence for skill groups and occupations". In: *The B.E. Journal of Economic Analysis & Policy* 11.1 (2011). URL: https://doi.org/10.2202/1935-1682.2615.

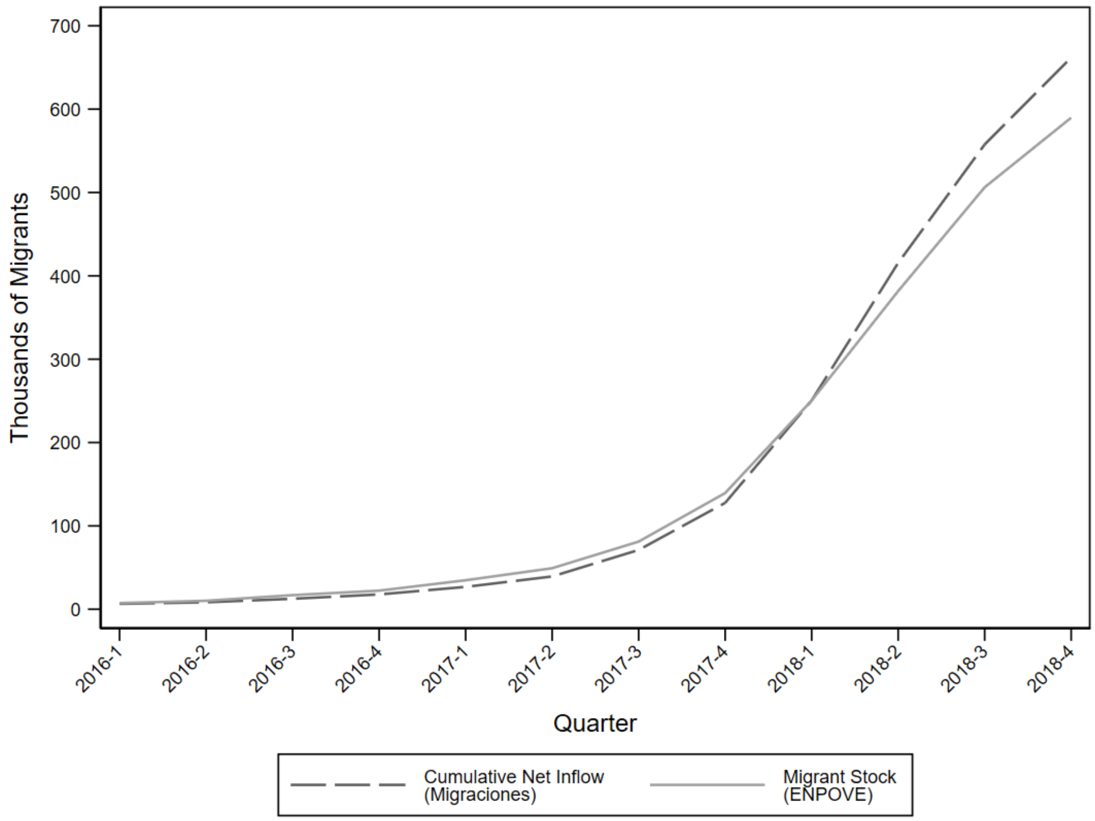
Tumen, Semih. "The economic impact of Syrian refugees on host countries: Quasi-experimental evidence from Turkey". In: *American Economic Review* 106.5 (2016), pp. 456–60. DOI: 10.1257/aer.p20161065.

United Nations High Commissioner for Refugees. *Forced Displacement in 2021*. Global Trends Report. 2022. URL: https://www.unhcr.org/publications/brochures/62a9d1494/global-trends-report-2021.html.

Vivatsurakit, Tanthaka and Jessica Vechbanyongratana. "Education–Occupation Mismatch and Its Wage Penalties in Informal Employment in Thailand". In: *Asian Development Review* 38.1 (2021), pp. 119–141. URL: https://doi.org/10.1162/adev_a_00160.

# Appendix

Figure A1: Venezuelan Migration in Peru. Comparison between ENPOVE and Migraciones




*Notes:* With ENPOVE data, the date of arrival has been used to calculate the number of Venezuelans in Peru in every quarter. If an individual arrived in quarter $t$, that individual is counted in all quarters after $t$. Counts are then calculated as the weighted counts of observations in every quarter. With Migraciones data, counts in quarter $t$ are calculated as $\text{entries}_t - \text{exit}_t + \text{cumulative net inflow}_{t-1}$.

Table A1: Recoding of Education Groups

| Peru (ENAHO) | Venezuela (ENPOVE) | Recode |
|---|---|---|
| No degree, Kindergarten, Elementary School, Some High School | No Degree, Kindergarten, Some Basic Education, Complete Basic Education, Some Diversified Education | High School Dropouts |
| High School Graduates, Some Non-College Higher Education | Diversified Education, Some Technical Education | High School Graduates or Some Technical Education |
| Complete Non-College Higher Education, Some College | Technical Education, Some College | Technical Education Graduates or Some College |
| College Degree, Masters' Degree/Ph.D. | College Degree, Masters' Degree/Ph.D. | College Graduates |

Table A2: The Effects of Immigration on Native Employment Using Occupation Cells, Using Sample Size with Positive Wages as Weigths

| | Formal Sector | | Informal Sector | | Overall | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Employment | Hours worked | Employment | Hours worked | Employment | Hours worked |
| OLS | -0.4133*** | -0.0063 | -0.0189 | 0.0101 | -0.0141 | 0.0070 |
| | (0.0582) | (0.0117) | (0.0329) | (0.0089) | (0.0164) | (0.0051) |
| IV | -0.3015*** | 0.0430** | -0.0409 | 0.0204 | -0.0273 | 0.0182** |
| | (0.0970) | (0.0213) | (0.0533) | (0.0147) | (0.0267) | (0.0086) |
| First stage estimates | 1.0499*** | 0.7833*** | 1.0499*** | 1.0311*** | 1.0499*** | 1.0499*** |
| | (0.1882) | (0.1427) | (0.1882) | (0.1980) | (0.1882) | (0.1882) |
| F-statistic | 31.13 | 30.12 | 31.13 | 27.12 | 31.13 | 31.13 |
| Observations | 60 | 53 | 60 | 54 | 60 | 60 |

Notes: The sample is employed men with 1-40 years of potential experience and positive wages (columns 5,6) and is further restricted to sector-specific employment in columns 1-4. Individuals with 0 hours of work are dropped from the sample only in the regressions of hours of work. The dependent variable is the change in the log number of employed natives (columns 1, 3, 5) or in the weekly hours worked in the main job (columns 2, 4, 6) in a given occupation. The independent variable is the log number of male immigrants working in a given occupation. In the 2SLS regressions, the number of immigrants in an occupation is instrumented with the former number of immigrants working in that occupation before migration. The specifications control for the average age and years of education of natives. Observations are weighted by the number of employed male natives with positive wages. Standard errors are reported in parentheses. $^{***}$ p< .01, $^{**}$ p< .05, $^{*}$ p < .1.

Table A3: The Effects of Immigration on Native Employment Using Occupation Cells, with Inverse Hyperbolic Sine Transformation to the Migrant Shock

| | Formal Sector | | Informal Sector | | Overall | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Employment | Hours worked | Employment | Hours worked | Employment | Hours worked |
| OLS | -0.0520 | -0.0118 | -0.0223 | 0.0102** | -0.0145 | 0.0056 |
| | (0.0409) | (0.0116) | (0.0232) | (0.0049) | (0.0156) | (0.0046) |
| IV | -0.1609** | 0.0247 | -0.0224 | 0.0212** | -0.0255 | 0.0192** |
| | (0.0731) | (0.0216) | (0.0377) | (0.0084) | (0.0261) | (0.0082) |
| First stage estimates | 0.8723*** | 0.8601*** | 1.1202*** | 1.1207*** | 1.0346*** | 1.0346*** |
| | (0.1709) | (0.1773) | (0.2118) | (0.2161) | (0.1943) | (0.1943) |
| F-statistic | 26.06 | 23.53 | 27.96 | 26.91 | 28.36 | 28.36 |
| Observations | 57 | 54 | 56 | 54 | 60 | 60 |

Notes: An inverse hyperbolic sine transformation (IHS) has been applied to the migrant shock and the dependent variables. For a random variable x, the inverse hyperbolic sine transformation is defined as (x $+\sqrt{x+1}$). The sample is employed men with 1-40 years of potential experience and positive wages (columns 5,6) and is further restricted to sector-specific employment in columns 1-4. Individuals with 0 hours of work are dropped from the sample only in the regressions of hours of work. The dependent variable is the change in the IHS of the number of employed natives (columns 1, 3, 5) or in the IHS of the weekly hours worked in main job (columns 2, 4, 6) in a given occupation. The independent variable is the IHS of the number of male immigrants working in a given occupation. In the 2SLS regressions, the number of immigrants in an occupation is instrumented with the former number of immigrants working in that occupation before migration. The specifications control for the average age and years of education of natives. Observations are weighted by the number of male natives used to compute the dependent variable. Standard errors are reported in parenthesis.$^{***}$ p< .01, $^{**}$ p< .05, $^{*}$ p < .1.

Table A4: Placebo Experiments. The Effects of Random Immigrant Shocks on Native Employment Using Occupation Cells

| | Placebo Experiment 1 | | | Placebo Experiment 2 | | | Placebo Experiment 3 | | | Placebo Experiment 4 | | | Placebo Experiment 5 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | Formal | Informal | Total | Formal | Informal | Total | Formal | Informal | Total | Formal | Informal | Total | Formal | Informal | Total |
| Extensive Margin | | | | | | | | | | | | | | | |
| OLS | -0.0085 | -0.0111 | -0.0146 | 0.0395* | 0.0337* | 0.0306*** | 0.0159 | -0.0030 | -0.0053 | 0.0128 | 0.0057 | -0.0038 | 0.0358 | 0.0048 | 0.0296* |
| | (0.0234) | (0.0231) | (0.0130) | (0.0225) | (0.0179) | (0.0106) | (0.0237) | (0.0196) | (0.0121) | (0.0226) | (0.0205) | (0.0121) | (0.0257) | (0.0281) | (0.0148) |
| IV | -0.0047 | 0.0339 | 0.0071 | 0.0433 | 0.0284 | 0.0300** | 0.0182 | -0.0188 | -0.0118 | 0.0250 | 0.0165 | 0.0091 | 0.0239 | -0.0768 | -0.0156 |
| | (0.0291) | (0.0388) | (0.0192) | (0.0333) | (0.0206) | (0.0130) | (0.0302) | (0.0230) | (0.0147) | (0.0263) | (0.0248) | (0.0146) | (0.0328) | (0.0469) | (0.0233) |
| First stage estimates | 0.7244*** | 0.5458*** | 0.6317*** | 0.7095*** | 0.8681*** | 0.8361*** | 0.7827*** | 0.8368*** | 0.8238*** | 0.8258*** | 0.7905*** | 0.8157*** | 0.7887*** | 0.5485*** | 0.6394*** |
| | (0.0811) | (0.1025) | (0.0935) | (0.1132) | (0.0790) | (0.0888) | (0.0921) | (0.0797) | (0.0826) | (0.0761) | (0.0826) | (0.0789) | (0.0938) | (0.0955) | (0.0960) |
| F-statistic | 79.69 | 28.38 | 45.64 | 39.31 | 120.65 | 88.71 | 72.28 | 110.39 | 99.55 | 117.83 | 91.59 | 106.78 | 70.65 | 32.98 | 44.36 |
| Observations | 57 | 56 | 60 | 57 | 56 | 60 | 57 | 56 | 60 | 57 | 56 | 60 | 57 | 56 | 60 |
| Intensive Margin | | | | | | | | | | | | | | | |
| OLS | 0.0036 | -0.0024 | 0.0008 | -0.0071 | 0.0016 | -0.0032 | 0.0014 | -0.0063 | -0.0033 | -0.0054 | -0.0072 | -0.0047 | 0.0013 | 0.0064 | 0.0012 |
| | (0.0046) | (0.0067) | (0.0041) | (0.0045) | (0.0053) | (0.0035) | (0.0047) | (0.0056) | (0.0038) | (0.0044) | (0.0058) | (0.0038) | (0.0052) | (0.0081) | (0.0048) |
| IV | 0.0064 | 0.0005 | 0.0020 | -0.0111 | 0.0010 | -0.0055 | -0.0074 | -0.0068 | -0.0058 | -0.0091* | -0.0133* | -0.0101** | 0.0039 | -0.0007 | 0.0027 |
| | (0.0058) | (0.0108) | (0.0060) | (0.0068) | (0.0061) | (0.0044) | (0.0062) | (0.0065) | (0.0046) | (0.0052) | (0.0071) | (0.0046) | (0.0067) | (0.0127) | (0.0070) |
| First stage estimates | 0.7239*** | 0.5455*** | 0.6317*** | 0.6982*** | 0.8683*** | 0.8361*** | 0.7836*** | 0.8368*** | 0.8238*** | 0.8276*** | 0.7910*** | 0.8157*** | 0.7876*** | 0.5457*** | 0.6394*** |
| | (0.0846) | (0.1046) | (0.0935) | (0.1185) | (0.0806) | (0.0888) | (0.0959) | (0.0812) | (0.0826) | (0.0788) | (0.0843) | (0.0789) | (0.0987) | (0.0978) | (0.0960) |
| F-statistic | 73.30 | 27.21 | 45.64 | 34.69 | 116.06 | 88.71 | 66.82 | 106.11 | 99.55 | 110.29 | 88.15 | 106.78 | 63.67 | 31.12 | 44.36 |
| Observations | 53 | 54 | 60 | 53 | 54 | 60 | 53 | 54 | 60 | 53 | 54 | 60 | 53 | 54 | 60 |

Notes: The results come from matching each endogenous regressor-instrument pair to a random native occupation using false identifiers. Each placebo experiment come from changing the randomization seed. The seeds used are arbitrary: 123, 1234, 711, 1206, and 2504. Each column represents a unique specification. The sample is employed men with 1-40 years of potential experience and positive wages (columns 3,6,9,12,15) and is further restricted to sector-specific employment in columns 1,2,4,5,7,8,10,11,13,14. Individuals with 0 hours of work are dropped from the sample only in the regressions in the lower panel. In the upper panel, the dependent variable is the change in the log number of male immigrants working in a given occupation. In the lower panel, the dependent variable is the change in the log weekly hours worked in the main job in a given occupation. The independent variable is the log number of male immigrants working in a given occupation. In the 2SLS regressions, the number of immigrants in an occupation is instrumented with the former number of immigrants working in that occupation before migration. The specifications control for the average age and years of education of natives. Observations are weighted by the number of male natives used to compute the dependent variable. Standard errors are reported in parenthesis.*** p< .01, ** p< .05, * p < .1.