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Migration Unit

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THE EFFECTS OF MASS MIGRATION ON NATIVES' WAGES. EVIDENCE FROM CHILE.*

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Abstract

Using cross-section data and an instrumental variable approach, this paper examines the mass migration process that occurred in Chile between 2015 and 2017. Evidence indicates that this process reduced wages for less skilled native workers by around 2-3 percent, mostly impacting males. These workers are competing with more educated immigrants, suggesting a downgrading effect. Results are robust to multiple IV tests.

Keywords: Immigration, Labour Market, Natives' Wages
JEL: J61, J31, F22

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1 Introduction

Over the last decades, migratory phenomena have become a key topic in most countries. In this context, the Latin America and the Caribbean (LAC) region has played a major role. According to the United Nations' 2017 International Migration Report, nearly 15% of the world's migrants arrive from this region. Even though 70% of LAC migrants reside in the USA, it is relevant to note that 16% of people migrate within this region, constituting the second most relevant destination.

Regarding this intra-regional migration, Chile is among the countries that have received the largest number of foreigners. More specifically, since 2015, Chile has received a large contingent of immigrants from Venezuela and Haiti. According to the 2017 Census, considering the 2015-2017 period only, said groups grew by 254% and 273% respectively.[1] According to the National Statistics Institute (INE), estimates for late 2018 place them as the first and third largest migrant bodies in Chile.

Undoubtedly, Venezuelans constitute the most emblematic example of intra-regional migration of the last years. In this regard, a 2018 report by the International Organization for Migration highlights that although Colombia, the USA, and Spain have received the largest absolute quantity of Venezuelan migrants, Chile has experienced the world's sharpest increase, with the number of people from that country displaying a 15-fold increase in the last 3 years. Chile's relative economic and political stability may be a possible influence on this migratory process.[2]

Therefore, Chile provides an interesting opportunity for empirically examining the consequences of rapid mass migration phenomena. Indeed, given Chile's small population, any effects of mass immigration phenomena should be statistically identifiable.

The empirical literature has examined the effects of migration on a variety of outcomes. More specifically, Lozano and Steinberger (2010) record at least 145 studies on the topics of migration and labour markets published between 1990 and 2010. Okkerse (2008), Longhi et al. (2005), and Dustmann et al. (2016) also provide good literature summaries, while at the same time outlining the main challenges and empirical differences involved in identifying the effects of migration. In this regard, the latter authors provide an excellent analysis of the differences found (mainly due to the theoretical and econometric specifications used) regarding the effect of migration on the native labor market.

Dustmann et al (2016) point out that there are three major approaches to measuring migration units. First, the skill-cell approach generally reports larger-magnitude negative effects. Borjas (2003) conducted one of the most relevant studies within this approach, finding that a 10% increase in the supply of migrants in skill-experience cells in the US reduces natives' salaries by 3% to 4% in the same cells. Second, the spatial approach generally reports lower-magnitude effects. Altonji and Card (1991), adopting this approach, find that a 1% increase in the share of migrants within an SMSA[3] in the US is linked to a 1.2% decrease in natives' salaries. Finally, the mixture approach combines the former two. Card (2001) exemplifies this approach, finding that the inflow of migrants to the US in the late 1980s reduced by 3% the relative salaries of the workers who were more exposed to competition from migrant workers (service workers and less-qualified workers) in cities with high migration rates.

Broadly speaking, the largest-magnitude effects revealed by the first approach are upwards-biased[4] (in absolute value) due to a

[1] Own calculation with 2017 Census data.

[2] As of this writing, Chile is undergoing a major political and social crisis that began in October 2019. The overcoming of inequality, a new pensions system, and a new political constitution rank among the main citizens' demands for resolving the crisis. This event, which local media outlets labeled Chile's "social eruption", had a strong impact on the inflow of migrants during the month when the protests started: according to the Department of Foreigners' Affairs and Migration, there was a negative migratory flow due to a reduction in Bolivian and Venezuelan immigrants. This is consistent with the view that Chile's prior political and social stability contributed to its status as a destination for intra-regional migration

[3] Standard metropolitan statistical area.

[4] Particularly in the US, according to Dustmann et al (2016).

downgrading effect, with more educated and experienced (i.e. more skilled) migrants competing with less-skilled natives. In general, the literature reports a negative but moderate effect of migratory flows on natives' salaries.

Despite the large amount of literature on migration, there is insufficient information about the effects of recent migratory shocks in developing countries. Studying migration in Chile can shed light on said effects. The relative size of the country, combined with the mass arrival of immigrants, provides an opportunity for identifying any possible consequences.

In this paper, we study the effects of recent migratory flows on natives' salaries in specific labor markets, represented by region-sector cells, thus adopting the mixture approach.[5] Classifying specific labor markets in region-sector cells makes it possible to avoid or at least reduce the problem of misclassification due to the downgrading effect. Also, to solve the endogeneity of the migratory flows in each region-sector cell, we performed two-stage least square estimations. As is usual in the literature, we used shift-share instrument to do this. Under this specification, immigrants tend to converge in economic sectors and regions with a high prior concentration of migrants from the same country.

Recently, this instrument has been subjected to major criticism. However, we have conducted several falsification and robustness tests that validate its use. Our results indicate that a 1% increase in the migrant rate in a region-sector cell, on average, is related with a 2.4% reduction in natives' salaries, but only in 2017, the year of the greatest migratory shock in recent Chilean history. In addition, it is in the subsample of men that the largest effect can be observed (a 2.9% reduction compared to a non significant 1.7% reduction for women). This effect appears to be driven by workers with a lower educational level, who display negative effects in all the years studied, especially in the male subsample. This negative effect is consistent with the literature and an unsurprising outcome of a sudden increase in immigration to a low-migration country such as Chile, which achieved relatively poor economic growth over the last decade.

This document is organized as follows: after this introduction, section 2 provides statistics about the recent migratory inflows in Chile, from both a local and an international perspective. Section 3 presents the methodology adopted in this study and the descriptive statistics of the data employed. Then, section 4 presents the results obtained, which are followed by our conclusions in the fifth and final section.

2 Recent immigrant inflows in Chile: Some statistics

In Latin America and the Caribbean, Chile is one of the countries that has received the most immigrants over the last years. Panel (a) of Figure 1 shows that the share of immigrants relative to the total population of Chile tripled between 2011 and 2017 (from 1.4% to 4.4%), with the total number of people whose mothers resided in another country when they were born increasing from 243,878 to 777,407[6], according to National Socioeconomic Characterization Survey (CASEN) data.

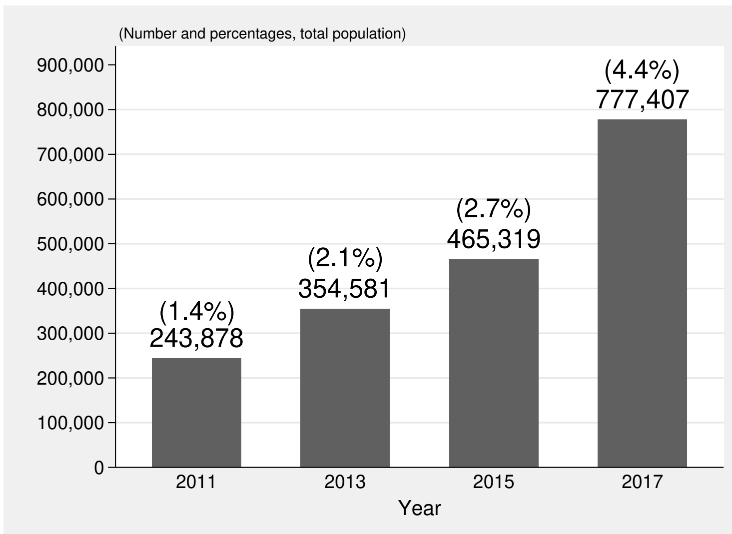
This trajectory is also characterized by the distribution of immigrants by country of origin. Figure 2 shows the evolution of the number of migrants in Chile for the six main communities, from 2011 to 2017. The graph has three salient aspects. First, the stable upwards trend of the population of Peruvian origin. Second, the drop in the relative importance of the Argentine colony, which was the second largest in 2011 and fell to the sixth place in 2017. Third, the rapid increase in Venezuelan and Haitian immigrants between 2015 and 2017, with the former becoming the largest colony in Chile (24.2% of the total number of migrants), surpassing the Peruvian community (22.2% of the total number of migrants) for the first time.

[5] In section 3, we discuss the virtues and limitations of this approach within the context of this study.

[6] Migrants are defined as people residing in a country different from that in which they were born, i.e people whose mothers gave birth to them in another country.

However, the graphs in Figure 8 (Appendix) show that even though Chile has a low percentage of migrants relative to OECD members (panel a), is among the top four countries in Latin America and the Caribbean in this regard (panel b) and, along with Colombia and Peru, has had some of the largest migrant inflows between 2015 and 2019. Figure 9 shows that Chile's migration rate evolved similarly to those of more developed (panel a) and high-income countries (panel b) between 1990 and 2019. Finally, Figure 10 compares the evolution of Chile's migrant rate with the rest of the world, revealing that it closely resembles that of Oceania, the continent with the highest migration rate.

Figure 1: Evolution of the number and percentage of migrants in Chile, 2011-2017



Source: 2011, 2013, 2015, and 2017 CASEN surveys. Calculations are performed using regional expansion factors as weights.

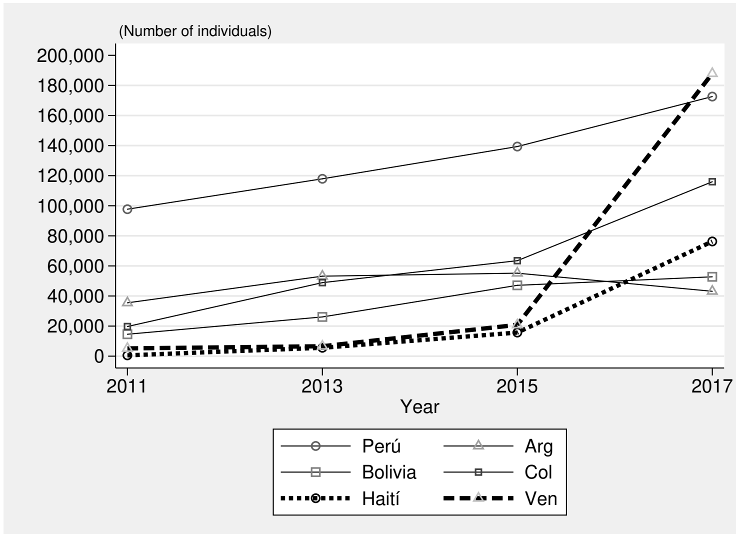
Given Chile's particular geography, the regional distribution of migrants is another relevant consideration. Table 1 shows the fraction of migrants relative to the entire population and the number of migrants in all regions of Chile. The table reflects that the fraction of migrants between regions is significantly heterogeneous. The Tarapacá Region stands out in this regard, as migrants constitute 13.9% of its population. This region is followed by the Antofagasta region (10.7%), the Arica and Parinacota Region (8.9%), and the Metropolitan Region (7.1%).

A recent report issued by the National Institute of Statistics (INE) states that, as of late 2018, four regions have a share of migrants of over 10%: Tarapacá (16.9%), Antofagasta (13.6%), Arica and Parinacota (10.4%), and Metropolitan (10.2%). A comparison between the 2017 census survey and the INE data (from late 2018) reveals that the share of migrants has increased significantly, especially in the Antofagasta Region, which rose from the third to the second place in a single year. This illustrates the constant growth of the migratory influx in all areas of the country.

The last two columns of Table 1 show the years of education of the workers in each region. The table also reveals that, in most regions (except for the 4 northernmost ones), immigrants have more years of education than natives. In this context, the large increase in migration from 2011 to date can have relevant consequences for the Chilean labour market. Before examining these possible effects, it is necessary to identify the sectors where migrants are finding jobs and determine the characteristics of these jobs.

As suggested by Altonji and Card (1991), if immigrants tend to work in the same sectors as a specific subgroup of natives, like those with a lower educational level, the effects of migration on this subgroup should be stronger.

Figure 2: Evolution of the number of migrants in Chile by country of origin, 2011-2017



Source: 2011, 2013, 2015, and 2017 CASEN surveys. Calculations are performed using regional expansion factors as weights.

To determine this, Table 2 shows the distribution of migrant workers along with the distribution of low-education natives, divided by economic activity (2-digit ciiu). These data show that migrants tend to occupy all sectors rather heterogeneously. The Table, which is sorted descendingly according to the distribution of migrants among sectors, shows that the Wholesale and Retail Commerce sector employs most migrant workers (21.9%), followed by Hotels and Restaurants (14.4%), Real Estate (12.3%), and Private Homes with Domestic Service (10.2%). All other sectors are under 10%. The fourth column shows the distribution of Chileans with at least 12 years of education (low skilled) in each economic sector. In general, Chileans with the lowest level of education tend to work in the sectors where migrants are most numerous. The distribution of low-schooling migrants in all sectors displays a similar pattern, as shown in the fifth column. Specifically, the wholesale and retail commerce sector –the main employer of migrants– concentrates the largest share of low-skilled natives and migrants. Finally, the last two columns show the average number of years of education of natives and migrants, with the latter surpassing the former in most cases.

In summary, recent statistical reports indicate that Chile's immigrant population has sharply increased and that it is heterogeneously distributed across the economic sectors, as migrants are concentrated in the areas that Chileans with the lowest educational levels occupy. Therefore, it is relevant to examine the possible consequences of this migratory phenomenon for local labour markets.

Table 1: Regional distribution of migrants in 2017.

Region	Migrants			Mean years ef education	
	Fraction	Total	Distribution	Natives	Migrants
Region I: Tarapacá	0,139	46,062	5,87%	12.21	11.50
Region II: Antofagasta	0,107	65,084	8,29%	12.62	12.19
Region III: Atacama	0,032	9,126	1,16%	12.02	11.29
Region IV: Coquimbo	0,021	15,739	2,01%	11.36	12.58
Region V: Valparaíso	0,025	44,636	5,69%	12.35	13.81
Region VI: O'Higgins	0,016	14,307	1,82%	11.19	12.89
Region VII: Maule	0,011	11,474	1,46%	10.78	14.18
Region VIII: Bio Bio	0,008	16,995	2,17%	11.78	13.63
Region IX: Araucanía	0,013	12,08	1,54%	11.25	13.90
Region X: Los Lagos	0,014	11,353	1,45%	11.21	12.21
Region XI: Aysén	0,022	2,312	0,29%	11.50	12.50
Region XII: Magallanes	0,045	7,563	0,96%	12.28	11.74
Region XIII: Metropolitana	0,071	503,611	64,18%	12.53	13.76
Region XIV: Los Ríos	0,011	4,272	0,54%	11.49	13.79
Region XV: Arica	0,089	20,071	2,56%	12.39	9.47
Total	0,045	784,685	100,00%	12.03	13.44

Source of migrant data: 2017 census data. Mean years of education are taken from Casen 2017 survey.

Table 2: Distribution of migrants among economic sectors, and of low-skilled natives and migrants (2017).

Sector	**N**	**% Migrants**	**Frac**	**% Low-Skilled**		**Mean years of education**	
				Natives	**Migrants**	**Natives**	**Migrants**
Wholesale and retail	110,830	21,89%	0,071	22,66%	23,35%	11.54	13.19
Hotels and restaurants	72,705	14,36%	0,184	4,77%	14,24%	11.83	13.29
Real estate and business activities	62,323	12,31%	0,105	4,61%	6,57%	13.93	15.21
Private homes with domestic service	51,815	10,24%	0,109	8,30%	12,95%	9.31	12.17
Manufacturing industries	47,490	9,38%	0,065	10,71%	12,06%	11.58	12.56
Construction	46,978	9,28%	0,067	11,18%	13,14%	10.79	12.08
Transport, storage, and communication	25,078	4,95%	0,044	8,16%	4,06%	11.95	14.28
Social and health care services	21,989	4,34%	0,049	2,56%	1,84%	14.82	16.11
Other community service activities	20,236	4,00%	0,068	3,32%	3,56%	12.78	13.79
Agriculture, livestock farming, hunting, forestry and fishing	17,975	3,55%	0,025	13,62%	5,47%	8.89	10.87
Teaching	13,337	2,63%	0,022	3,47%	1,25%	15.10	15.27
Finance	6,303	1,25%	0,051	0,70%	0,28%	14.73	16.59
Public administration and defense	5,388	1,06%	0,014	3,52%	0,54%	13.72	15.50
Exploitation of mines and quarries	2,549	0,50%	0,018	1,70%	0,53%	12.98	12.63
Electricity, gas, and water supply	800	0,16%	0,014	0,71%	0,15%	12.61	13.66
Extraterritorial organizations and bodies	438	0,09%	0,517	0,00%	0,00%	14.66	17.16
Total	506,234	100,00%	0,065	100,00%	100,00%	12.03	13.44

Source: CASEN 2017. Calculations are performed using regional expansion factors as weights. Low-skilled defined as having equal or less than 12 years of schooling.

3 Methodology

3.1 Empirical identification

This study is aimed at shedding light on the impacts of migration in Chile. Specifically, it identifies and analyzes the effects of recent massive migration on the salaries of native workers, both overall and specifically for lower-skilled ones. In order to achieve this goal, the proposed methodology is represented by the following equation:

$$Y_{i,t} = \alpha + \delta \ln(MR_{rs,t}) + \gamma LS_i + \beta \ln(MR_{rs,t}) * LS_{i,t} + X_{i,t}\rho + \lambda_r + \lambda_s + \varepsilon_{i,t} \tag{1}$$

Where $Y_{i,t}$ is the nominal hourly wage (in logs) of native individual i, while $\ln(MR_{rs,t})$ is the natural logarithm of the migrant workers' rate in sector s and region r. The variable $LS\,(Low\,Skills)$ is a *dummy* that indicates whether individual i has a level of accumulation of human capital of 12 years of education, at most.[7] The interest coefficient is parameter β, which accompanies the interaction between $\ln(MR_{rs,t})$ and LS and is interpreted as the effect of a 1% increase in the inflow rate of migrant workers on the salaries of low-education natives, compared to those with a higher education level.[8] To calculate the total effect of migration, we take the derivative of (1) with respect to $\ln(MR_{rs,t})$, i.e. $\hat{\delta} + \hat{\beta}\bar{LS}$. For its part, $X_{i,t}$ is a vector of individual variables such as sex, years of education, potential experience, and its square. We also add regional and economic sector fixed effects, denoted by the terms λ_r and λ_s, respectively. Lastly, α is the intercept and $\varepsilon_{i,t}$ is the error term. All variables are measured in period t. This equation will be estimated from CASEN survey data from the 2013, 2015, and 2017 waves, separately, for both the full sample and by gender. This is an individual level cross-section database that will be described in section 3.3.

Note that (1) represents the mixture approach discussed in the introduction. In this regard, there were many reasons for selecting migration rates in region-sector cells to identify the impact of migration on native wages. First, this choice was made due to the high variation in the value of this last variable between each cell, as shown in Tables 1 and 2. Second, we believe that region-sector cells manage to identify more specific labor markets where the level of competition between natives and migrants is much greater. Third, even though the downgrading effect may cause bias in the estimated coefficients (Idem), this would be a second order bias, since the cell in economic sectors is a labour market that provides a larger margin for competition between natives and migrants with different educational and experience levels.

Dustmann et al. (2016) note that the national-skill cell approach assumes that the competition between natives and migrants occurs at a specific skill level of each party. Thus, for a specific skill-experience cell, it is necessary to calculate both the immigration rate and the salary of the natives in it; however, due to the possibility of downgrading, migrants with a specific skill-experience level do not compete with natives from the same cell, but with others from lower levels. Therefore, the migrant rate calculated for a skill-experience cell does not represent the actual migrant rate affecting natives in a given level, i.e. there is a misclassification of the true competition parameter affecting natives in each cell measured according to years of schooling, experience, etc. The mixture approach used in this paper is determined by economic sector and region and is not strictly restricted by schooling or experience, which results in a much larger cell that can lead to categorizing differently-skilled workers at the same level. The

[7] In Chile, it is mandatory for students to attend school for 12 years. According to national and comparative evidence (OECD), most Chilean students acquire low-quality knowledge. Indeed, Chile is among the countries with the lowest PISA scores. Consistently, returns on education have a convex pattern in the country, with tertiary education displaying the highest returns. Therefore, the 12-year mark (full secondary education) is used to define low-skilled workers.

[8] Although logarithmically expressed rates are infrequent in the literature, they are used in this paper for three reasons. First, to make it possible to interpret the data more intuitively in terms of an elasticity. Second, given that migration rates are rather low in each region-sector cell, the distribution of the logarithms appears to behave better, tending to resemble a normal distribution (see Figures 8 to 10 in the Appendix). Lastly, using these rates to estimate the coefficients yields counter-intuitive and unconvincing results (i.e. extremely high coefficients); in contrast, using logs yields values more consistent with the literature, as shown in the Results section.

problem of misclassification is thus rather minor. For instance, in the Social and health care services sector, an immigrant who was a physician in her country of origin but works as a nurse in her adoptive country (the canonical example of downgrading) would be competing with a native who works in that sector (a nurse), but both native physicians and nurses would be exposed to the same migrant shock (since the migrant rate is defined in region-sector cells). Here lies the importance of the interaction with the dummy *LS*: this makes it possible to capture the specific effect within the cell for low-skilled workers relative to high-skilled ones. In sum, by measuring the immigration rate in sector-region cells, we are applying the usual mixture approach of the literature in a way that is less strongly affected by the misclassification problem due to the downgrading effect. However, since this approach measures the effect of immigration on natives without considering their skills, it is necessary to calculate the interaction between the immigration rate in the cell and the low-skill status of the native working in it.

Given the endogeneity of variable $MR_{rs,t}$, which is potentially biased by immigrants' chosen region of residence, we propose using an instrumental variable, similar to that employed in the literature[9]. This variable is constructed as follows:

$$Z_{rs,t} = \frac{\sum_c \frac{M_{crs,02}}{M_{c,02}} * \sum_{t_0}^{t} M_{ct}}{Pop_{rs,t}}$$

Where $M_{crs,02}$ is the number of migrants from country c working in sector s of region r in 2002, and $M_{c,02}$ is the total number of immigrants from country c in 2002 at a national level. So, $\frac{M_{crs,02}}{M_{c,02}}$ is the share of migrants from country source c, working in region-sector cell rs in 2002, relative to the total number of migrants from their country. Then, $\sum_{t_0}^{t} M_{ct}$ is the stock of migrants from country c at a national level, between 2005 (t_0) and t. Finally, $Pop_{rs,t}$ is the total number of workers in region-sector cell rs at time t.[10] This is the shift-share instrument used in the literature, which is similar to the *supply-push* component suggested by Card (2001).

The use of this instrument is consistent with the fact that migrants tend to be drawn to cities with a high prior concentration of migrants (Bartel, 1989; Greenwood & McDowell, 1986). Following the same idea, immigrants are likely to be clustered in economic sectors with a high prior concentration of migrants. We selected 14 places of origin, grouped on the basis of ethnic and geographical similarity: the largest migrant communities (6) namely Venezuela, Haiti, Peru, Colombia, Bolivia, and Argentina; and the other continents and regions of the world (8) namely Africa, South America, North America, Central America, The Caribbean, Oceania, Asia, and Europe.

Then, the first stage is estimated as follows:

$$\widehat{MR}_{irs,t} = \pi_0 + \pi_1 Z_{rs,t} + X'_{irs,t}\pi_2 + \lambda_r + \lambda_s + \nu_{irs,t} \tag{2}$$

Where vector $X'_{irs,t}$ includes the same control variables as (1), but an interaction between $Z_{rs,t}$ and *LS* is added as well as *LS* by itself. In (2), π_0 is the intercept, λ_r and λ_s are the fixed effects by region and sector, respectively, and $\nu_{irs,t}$ is the error term. From (2), we

[9] This literature includes studies by Altonji and Card (1991) and Card (2001). For instance, in the first study, the authors use the percentage of migrants in each U.S. city in 1970 as an instrument of the same percentage for 1980.

[10] This variable is also instrumentalized much like in Mayda et al. (2018):

$$\widehat{Pop}_{rs,t} = \widehat{M}_{rs,t} + \widehat{N}_{rs,t}$$

Where,

$$\widehat{M}_{rs,t} = sh_{M,rs,02} M_t \ y \ \widehat{N}_{rs,t} = sh_{CH,rs,02} N_t$$

The term $sh_{M,rs,02}$ is the share of migrants who worked in region r and sector s relative to the total number of migrants in 2002 (according to census information), whereas $sh_{CH,rs,02}$ is the share of Chileans who worked in the region-sector cell rs relative to the total number of Chilean workers in 2002. By using this instrumentalized variable in the denominator of $Z_{rs,t}$, the latter becomes less robust to the falsification tests (available upon request) analyzed in section 4.2, but coefficient β from the second stage remains robust in terms of sign and significance (see Table 9 in the Appendix).

calculate the means of the predicted value of $\widehat{MR}_{irs,t}$ at region-sector cell level ($\widehat{MR}_{rs,t}$) and then included in natural logarithm to equation (1) to estimate coefficient β and $\hat{\delta}+\hat{\beta}\bar{LS}$ without bias.

3.2 Threats to identification

Although the shift-share instrument has been extensively used in the literature on migration, it has received criticism especially regarding its failure to meet the exclusion condition. Jaeger et al. (2018) present evidence that this instrument has trouble identifying the timing of the effects calculated in labour markets in the presence of migratory flows. That is, it does not unambiguously indicate whether the effects of migratory shocks are short- or long-term. According to the authors, this is caused by the interaction of two factors: (i) that certain conditions in local labour markets may be correlated with migratory flows and (ii) that the composition of immigrants' countries of origin and their settlement patterns correlate over time, which causes the same cities to be chosen by immigrants in each new inflow. Factor (i) essentially means that, if migrants are attracted to labour markets with better salaries, for example, these high salaries can offset the short-term negative effect of a migratory shock on natives; while (ii) indicates that, since these flows can be strongly time-related, the instrument might be capturing long-term adjustments as responses to prior migratory shocks.

Given the identification problems derived from (i), we performed two tests to validate the use of the shift-share instrument based on Mayda et al. (2018)[11] and also suggested by Goldsmith et al. (2019). First, we regressed the change between migration rates, both the current ones and those predicted at the level of region-sector cells, on the average salary in each cell in the past. This was done to establish whether the prior salary in a region-sector cell has any predictive power regarding changes in migration rates in later periods, thus making it possible to rule out the possible influence of each cell's prior economic conditions on the current settlement of migrants in them, beyond the prior settlement of migrants from the same country of origin.[12] Second, we regressed the change in the migration rate predicted by the instrument on the prior and current change in the salaries at the region-sector cell level, which helps to test the exclusion condition of the share-shift instrument, as long as the predicted rates are unrelated to trends in the past or contemporary economic conditions (where average salary is a proxy) of each sector.[13] In both cases, if the coefficient of interest in these regressions is close to 0 and/or statistically non-significant, the use of the shift-share instrument is validated. The results of the tests mentioned here are presented in the following section.

Finally, the most serious problems of the shift-share instrument analysed by Jaeger et al. (2018) concern the second factor mentioned above. However, these authors also mention that, as long as the lag in the share of migrants from each country is sufficiently long, and as long as both the distribution of migrants across cities and their places of origin are not too stable over time, it is more likely for the instrument to fail to capture long-term adjustments related to prior migratory flows. This appears to be the case regarding the recent history of migratory flows in Chile. First, the composition of immigration flows by country of origin has undergone major changes, especially considering the 2015-2017 period. Indeed, this period is marked by the migrant shock originating in Venezuela and Haiti, as shown in Figure 2.[14] Also, far from remaining stable, the national migration rate has increased every year (Figure 1). Furthermore, the descriptive statistical data presented in the following section displays a sufficient level of variation in terms of the

[11] In an more recent version of these work, the authors only keep the second falsification test, which is a more direct test due to the exclusion restriction.

[12] In Mayda et al. (2018), the authors examine how immigration into the USA influenced the proportion of Republican Party votes at a county level from the 1990s to the 2010s. They find that increases in the rate of high-skilled (low-skilled) migrants correlate with reductions (increases) in the percentage of Republican Party votes, according to both OLS and 2SLS. They use a shift-share instrument in their 2SLS estimation. To test whether the instrument corrects double causality problems (e.g. that counties which are more likely to vote Republican attract (reject) low-skilled (high-skilled) immigrants, the authors regress the change in the percentage of migrants in these counties over a decade on the percentage of Republican votes (the dependent variable) in the prior decade.

[13] In Mayda et al. (2018), this consists in testing whether changes in the migration rate predicted by the shift-share instrument correlates with previous or contemporary changes in local economic and demographic conditions (rural population share, unemployment rate, per capita income, exposure to international commerce shocks).

[14] A similar exercise is presented in Tabellini (2019).

distribution and percentage of migrants across regions and economic sectors in all the years under examination. Finally, the use of the year 2002 to select the past share of migrants in the instrument is broad enough to avoid exogeneity problems regarding natives' salaries in each labour market more than one decade later (from 2013 onwards).[15]

3.3 Data

The data to be used to study the effect of migration on natives' wages (equations (1) and (2)) come from the National Socioeconomic Characterization Survey (CASEN), an individual level cross-sectional public database updated biannually since 1985. It is a representative database of Chilean homes at the country level and contains a wide range of variables that identify the sociodemographic characteristics of the Chilean population.

To estimate equation (2) in the first stage, the instrument $Z_{rs,t}$ is constructed as follows: the past share of migrants in the region-sector cell is calculated with 2002 census data. Then, the stock of migrants in period t ($\sum_{t_0}^{t} M_{ct}$) is constructed with 2017 census data. Since this information is collected for immigrants living in Chile in 2017, this indicator excludes the flow of immigrants who left before that year. This configures a possible limitation of the instrument that must be pointed out. Finally, the term $Pop_{rs,t}$ is generated with regional expansion factors as weights from CASEN survey data.[16]

The second stage (equation (1) with the predicted values of the first stage) will be estimated using CASEN survey data from the 2013, 2015, and 2017 waves, separately. In addition, equation (1) will be separately estimated in restricted samples of men and women in order to identify possible heterogeneous effects by sex.

3.4 Descriptive Statistics

Table 3 presents descriptive statistics for the variables used in this paper, separated according to the wave of the CASEN survey to which they belong. The sample is restricted to working individuals between 15 and 65 years old. This table shows that the percentage of women is quite stable among both natives and migrants, with slight increases among natives and a modest decrease among migrants. Years of education went up between 2013 and 2015 for both groups, with migrants surpassing natives by slightly more than one year, which is a non-trivial difference. As for age, natives are approximately 4-7 years older than migrants in general during the period analysed; also, while natives are becoming slightly older, the average age of migrants is gradually decreasing. In line with the latter two variables, natives have more years of potential experience, as the average number of years of experience went down among migrants between 2015 and 2017.

[15] The literature that employs the shift-share instrument tends to use lags of up to one decade in migrant distribution.

[16] We also built the variable $Pop_{rs,t}$ according to the 2017 Census. However, we prefer the CASEN survey because the census does not make it possible to establish the exact number of people in the region-sector cells for the years prior to 2017.

Table 3: Descriptive Statistics

	2013		2015		2017	
	Natives	Migrants	Natives	Migrants	Natives	Migrants
Individual Characteristics						
Women = 1	0.423	0.493	0.436	0.468	0.439	0.466
Years of schooling	11.786	13.034	12.035	12.812	12.224	13.460
Age	40.544	36.328	40.955	35.888	41.558	34.273
Potential Experience	22.846	17.352	23.010	17.134	23.422	14.870
Low Skills = 1	0.668	0.584	0.645	0.606	0.623	0.520
Regional Distribution						
Tarapacá	0.017	0.049	0.017	0.064	0.017	0.055
Antofagasta	0.031	0.072	0.030	0.064	0.032	0.044
Atacama	0.016	0.009	0.015	0.009	0.016	0.005
Coquimbo	0.041	0.024	0.040	0.019	0.038	0.013
Valparaíso	0.099	0.058	0.101	0.044	0.103	0.041
Libertador Gral. Bdo. O'Higgins	0.053	0.013	0.054	0.008	0.054	0.015
Maule	0.058	0.007	0.059	0.005	0.059	0.011
Biobío	0.107	0.017	0.108	0.009	0.111	0.024
Araucanía	0.051	0.014	0.051	0.013	0.053	0.010
Los Lagos	0.049	0.015	0.049	0.009	0.051	0.011
Aysén	0.006	0.003	0.006	0.003	0.007	0.003
Magallanes y de la Antártica Chilena	0.010	0.004	0.010	0.006	0.010	0.007
Metropolitana de Santiago	0.436	0.694	0.431	0.726	0.422	0.745
Los Ríos	0.019	0.003	0.020	0.006	0.020	0.003
Arica y Parinacota	0.009	0.018	0.009	0.013	0.008	0.013
Distribution by Sector						
Agriculture, livestock farming, hunting, forestry, and fishing	0.093	0.026	0.096	0.025	0.094	0.035
Exploitation of mines and quarries	0.029	0.012	0.027	0.017	0.019	0.005
Manufacturing industries	0.113	0.102	0.096	0.088	0.093	0.094
Electricity, gas, and water supply	0.006	0.003	0.007	0.004	0.008	0.002
Construction	0.096	0.091	0.092	0.114	0.090	0.093
Wholesale and retail	0.190	0.179	0.192	0.208	0.198	0.218
Hotels and restaurants	0.042	0.111	0.043	0.128	0.045	0.144
Transport, storage, and communication	0.079	0.072	0.076	0.043	0.074	0.050
Finance	0.018	0.019	0.018	0.013	0.017	0.012
Real estate and business activities	0.065	0.091	0.070	0.076	0.073	0.123
Public administration and defense	0.044	0.012	0.052	0.016	0.054	0.011
Teaching	0.080	0.041	0.085	0.044	0.082	0.026
Social and health care services	0.055	0.052	0.054	0.047	0.060	0.043
Other community service activities	0.030	0.052	0.031	0.053	0.038	0.040
Private homes with domestic service	0.061	0.135	0.059	0.123	0.056	0.103
Extraterritorial organizations and bodies	0.001	0.003	0.000	0.002	0.000	0.001

Source: Own calculation with 2013, 2015, and 2017 CASEN survey waves. Expansion Factors at a regional level are used as weights. The sample in each wave is restricted to employed individuals between 15 and 65 years old.

The regional distribution of both groups also displays major differences. Natives' distribution remains stable throughout the three years studied. However, migrants display much more variability, with the share of migrants relative to the national total increasing in regions like Tarapacá between 2013 and 2015, but going down between 2015 and 2017. A different situation is observed in the BioBío and Los Lagos regions, where the share of migrants goes down in the first two-year period but increases in the last. The Metropolitan Region, where the Chilean capital is located, has constantly increased its share of the total number of migrants in the country, concentrating nearly three quarters in the period examined.

A similar situation is observed with respect to the distribution across economic sectors: natives have been much more stable in terms of their levels of participation in each sector over the years, whereas migrants' occupations have proven much move variable. More specifically, migrant participation in private homes with domestic service has decreased, but has increased considerably in wholesale and retail.

Figure 6 (Appendix) shows the percentage of migrants relative to the total population aged 15-65 for the three years studied, separated by region and economic sector. The result is similar to that presented in the previous table: the percentage of migrants has varied in all sectors and regions, with a high level of heterogeneity. Nevertheless, it is clear that the share of migrants increased in all these cells between 2013 and 2017, which is a direct consequence of the increase of the rate of migrants in the same period.

In sum, major differences exist between migrant and native groups. Migrants tend to have more years of schooling, be younger, and have less experience than natives, while their distribution across regions and economic sectors is more volatile than that of natives in each of the years examined.

4 Results

4.1 OLS and 2SLS Estimates

Table 4 shows the results of equation (1), estimated using OLS. Panel A shows the results of the interaction between the variable of interest and the Low Skills dummy. Columns 1, 4, and 7 present the results of the estimation of the whole sample of natives aged 15-65 years. Results indicate that a 1% increase in the rate of migrants working in each region-sector cell correlates with a 4.8% reduction in the nominal hourly salary of low-skilled native workers compared to high-skilled ones in 2013, a weakly significant 1.2% reduction in 2015, and a 2% reduction in 2017. The above result is clearly explained by the effect on the subsample of men, as shown in columns 2, 5, and 8.

Likewise, Panel B of Table 4 shows the total effect of the migration rate in each region-sector cell on the salaries of natives working in them. Although the effects on the full sample are smaller and less significant in the first years, 2017 marks a departure from this trend, with natives' salaries rising by 3.0%. In contrast with Panel A, it is women rather than men who seem to propel this effect.

However, since migrants do not arrive in random labour markets, OLS estimates may be biased. If migrant workers are attracted by firms that offer better salaries, there may be an upwards bias affecting natives' salaries as long as their salaries are higher than those offered by companies where migrants are less likely to work.

Table 4: Effects of region-sector share of migrants on log wages of native workers (OLS).

	2013			2015			2017		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Full	Men	Women	Full	Men	Women	Full	Men	Women
Panel A: OLS Estimation									
$\ln(MR_{rs,t})$	0.040***	0.083***	-0.015	0.018**	0.022*	0.014	0.042***	0.045***	0.039***
	(0.013)	(0.017)	(0.019)	(0.008)	(0.011)	(0.011)	(0.009)	(0.012)	(0.013)
$LS = 1$	-0.510***	-0.672***	-0.291***	-0.343***	-0.429***	-0.233***	-0.341***	-0.405***	-0.266***
	(0.049)	(0.069)	(0.067)	(0.027)	(0.037)	(0.040)	(0.029)	(0.041)	(0.043)
$\ln(MR_{rs,t}) \times LS$	-0.048***	-0.081***	-0.004	-0.012**	-0.026***	0.004	-0.020***	-0.034***	-0.005
	(0.011)	(0.016)	(0.015)	(0.006)	(0.008)	(0.009)	(0.007)	(0.010)	(0.010)
Observations	73,928	44,297	29,631	95,038	55,946	39,092	77,863	44,600	33,263
Adjusted R-squared	0.310	0.313	0.300	0.313	0.322	0.293	0.297	0.302	0.289
Panel B: Total effect									
$\frac{\partial Y_{irs,t}}{\partial \ln(MR_{rs,t})} = \hat{\delta} + \hat{\beta}\bar{LS}$	0.005	0.022*	-0.018	0.009	0.002	0.016**	0.030***	0.022**	0.036***
	(0.009)	(0.012)	(0.015)	(0.006)	(0.008)	(0.008)	(0.007)	(0.009)	(0.010)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample is restricted to natives between 15 and 65 years old. The control variables of the estimation are years of schooling, potential experience and its square, a dummy of women (in the full sample), and region and sector fixed effects. Regional expansion factors are used as weights.

Table 5 shows the results of equation (1), estimated with 2SLS, using the shift-share instrument as exclusionary variable in the first stage, represented by equation (2). Columns 1, 4, and 7 of panel A present the results of the whole-sample estimation. Here, results indicate that a 1% increase in the rate of migrants working in region-sector cells correlates with a 2.6% decrease in the nominal hourly salary of low-skilled native workers compared to high-skilled ones in 2013, a 1.2% reduction in 2015, and a 2.4% reduction in 2017. It should be noted that the estimated coefficients are quite similar to those yielded by the OLS method, except for the 2013 estimation, where they decrease by almost a third. Also, like for the OLS method, this result is mainly led by the effect on men, as shown in columns 2, 5, and 8. Here, the increase in the migrant rate correlates with 6.2%, 2%, and 3.1% reductions in 2013, 2015, and 2017 respectively. Note that there is no difference between the effect of migration rates in low skilled relative to high skilled woman in all years under study.

Panel B of Table 5 shows the total effect of migration, controlling for the endogeneity of this variable. There more important effects, in terms of magnitude, are the results from 2017, the last year under examination. However, using the 2SLS method instead of OLS causes the effect to become negative: a 1% increase in the rate of migrant workers in the region-sector cell causes a 2.4% decrease in the salaries of native workers in 2017. The decrease amounts to 2.9% for men and 1.7% for women, no significant in statistics terms for this last subsample.

In addition, it is interesting to consider the behavior of the coefficient associated with the variable *LS*. In men, it decreases over time in all the years studied, which appears to reflect a gradual reduction in the salary gap between high-skilled and low-skilled natives: low-skilled native workers earned 60% less than their high-skilled peers in 2013, but the difference drops to 40% in 2017. For women, the situation is the opposite: in 2013, less qualified women earned 26% less than those with a higher educational level, but the difference is even greater in 2017, with the gap reaching 30%.

Finally, Panel C of Table 5 shows the results of the first stage. F-test of the instrument, despite yielding progressively lower values, remains above 10 in all estimations throughout the period examined. Likewise, very high values are obtained when F-test of the interaction is also considered, thus validating the relevance of the instrument. As expected, the coefficient of the instrument is positive. Figure 7 (Appendix) illustrates the the migrant rate in the region-sector cell as predicted by the instrument and its value in 2017, which clearly indicates that they are strongly associated.

Table 5: Effects of region-sector share of migrants on log wages of native workers (2SLS).

	2013			2015			2017		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Full	Men	Women	Full	Men	Women	Full	Men	Women
Panel A: Second Stage									
$\ln(\widehat{MR}_{rs,t})$	0.022	0.071*	-0.013	0.000	0.011	-0.011	-0.006	-0.003	-0.007
	(0.020)	(0.042)	(0.013)	(0.008)	(0.011)	(0.011)	(0.009)	(0.013)	(0.012)
LS	-0.433***	-0.607***	-0.259***	-0.343***	-0.403***	-0.279***	-0.357***	-0.398***	-0.305***
	(0.052)	(0.093)	(0.048)	(0.026)	(0.036)	(0.038)	(0.031)	(0.044)	(0.047)
$\ln(\widehat{MR}_{rs,t}) \times LS$	-0.026**	-0.062***	0.004	-0.012**	-0.020**	-0.005	-0.024***	-0.031***	-0.017
	(0.012)	(0.023)	(0.010)	(0.006)	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)
Observations	73,159	43,828	29,331	84,959	50,484	34,475	70,557	40,852	29,705
Adjusted R-squared	0.311	0.317	0.300	0.309	0.320	0.282	0.294	0.301	0.282
Panel B: Total Effect									
$\frac{\partial Y_{irs,t}}{\partial ln(MR_{rs,t})} = \hat{\delta} + \hat{\beta}\bar{LS}$	0.003	0.023	-0.010	-0.008	-0.004	-0.014	-0.024***	-0.029**	-0.017
	(0.013)	(0.026)	(0.010)	(0.006)	(0.008)	(0.010)	(0.008)	(0.011)	(0.014)
Panel C: First Stage									
$Z_{rs,t}$		0.393***			0.238***			0.042***	
		(0.009)			(0.015)			(0.005)	
$Z_{rs,t} \times LS$		-0.001			0.198***			0.067***	
		(0.008)			(0.012)			(0.005)	
Total effect		0.392***			0.262***			0.172***	
		(0.057)			(0.010)			(0.004)	
Observations		81,932			101,708			81,585	
Adjusted R-squared		0.820			0.827			0.899	
F-test $Z^1_{rs,t}$		1712.01			228.97			60.7	
F-test $Z^1_{rs,t} + Z^1_{rs,t} \times LS$		2454.98			348.18			1421.56	

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample is restricted to natives between 15 and 65 years old. The control variables of the estimation are years of schooling, potential experience and its square, a dummy of women (in the full sample), and region and sector fixed effects. Regional expansion factors are used as weights.

4.2 Checking the validity of the instruments.

Given the recent criticism leveled at the shift-share instrument, the latest research on migration has attempted to demonstrate its validity using a number of strategies. In Tables 7 and 8 of the appendix, we conduct two tests to validate its use, as mentioned in the previous section.[17]Only the second test is included in the most recent version of Mayda et al. (2018).

In Table 7 of the appendix, we conduct the first test to support the validity of the use of the shift-share instrument. In this case, the dependent variable is the change in the share of migrants at the region-sector cell level between 2013 and 2015 (columns 1 to 3) and between 2013 and 2017 (columns 4 to 6). The variable of interest is the average hourly salary in each cell in 2011, and the estimations are conducted considering region-sector cells as a unit of observation. Three models are generated: without controls, with control variables (average experience in the cell and its square and average schooling) and with control variables and region and sector fixed effects. Panel A shows the results considering changes in rates, revealing that no coefficients are statistically significant and that they are all near zero in terms of magnitude. In the same table, Panel B shows the results of the change in the migration rate predicted by the shift-share instrument. Again, there are no significant effects in any of the models. In our preferred estimation, which includes controls as well as region and sector fixed effects (columns 3 and 6), the magnitude of the coefficient is even smaller in absolute terms (closer to 0) in both cases. Therefore, prior salary levels in region-sector cells do not explain the change in the migration rate during the periods being analysed. This means that, even though migrant workers do not enter specific markets at random, the lag in the salaries paid in each cell does not appear to be systematically correlated with the distribution of migrants among these markets in subsequent years.

[17]red

Table 8 shows the results of the second test aimed at validating the use of the shift-share instrument. In this case, we regress the change in the share predicted by our shift-share instrument between 2015 and 2017 on the change in the hourly salary in the region-sector cell[18] between 2011 and 2013 (previous trends) and between 2015 and 2017 (contemporary trends), with and without controls, and adding controls and region and sector fixed effects. Panel A shows that there is no association between predicted changes in rates and prior economic trends in the labour markets defined in the region-sector cells. Panel B reflects the same situation, but indicating that there is no association with changes in contemporary economic trends. In sum, the shift-share instrument is robust regarding the prior and contemporary evolution of economic conditions in each labour market; that is, results yielded by the 2SLS method do not appear to be explained by said factors.

Lastly, the great heterogeneity in migrants' countries of origin, along with the high variability in their distribution and concentration across Chile's regions and economic sectors, make it very hard for the instrument to capture the long-term effects of market adjustments to migration, as suggested by Jaeger et al. (2019). Both this and the results of the two tests conducted confirm that the shift-share instrument can be used to control for the endogeneity of the recent mass inflow of migrants into Chile's region-sector cells.

4.3 Downgrading effect

Section 2 showed that, in most regions and in most economic sectors, the average immigrant has more years of schooling than his/her native peers (Tables 1 and 2). In fact, in more than three fourths of the more than 200 cells, immigrants have more years of schooling than natives for the year 2017. This suggests that the results shown in Table 5, where the effect of immigration rates is negative on low-skilled workers relative to high-skilled ones, are led by a downgrading effect: native workers compete with more highly skilled immigrant workers in local labor markets.

Table 6 shows the results of the estimates for the year 2017 through 2SLS, restricting the estimations according to the region-sector cells where immigrants have fewer years of schooling than natives (odd columns - $ESC_{rs}^{N} > ESC_{rs}^{M}$) and restricting the estimations in cells where immigrants have more years of schooling than natives (even columns - $ESC_{rs}^{N} < ESC_{rs}^{M}$). The results presented in this table suggest that the negative consequences of higher immigrant rates in region-sector cells affecting low-skilled workers relative to high-skilled ones (see last 3 columns of Table 5) are only observed in region-sector cells where immigrants have more years of schooling than natives. In contrast, in cells where the opposite is true (natives with more years of education than immigrants), coefficient β is positive but non-significant. The results of the women subsample also yield a non-significant coefficient β.

[18]Unlike Mayda et al. (2018), who use counties as their unit of observation, we are unable to evaluate any of the units that they use at the cell level. For this reason, our proxy for economic conditions is the salary in each cell. Nevertheless, this is not a serious limitation since the main difficulties in identifying the effect of migrants on local labour markets are related to the potential attractiveness of these markets for migrants due to the salaries offered.

Table 6: Effects of region-sector share of migrants on log wages of native workers (2SLS - downgrading effects).

	Full		Men		Women	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$ESC_{rs}^{N} > ESC_{rs}^{M}$	$ESC_{rs}^{N} < ESC_{rs}^{M}$	$ESC_{rs}^{N} > ESC_{rs}^{M}$	$ESC_{rs}^{N} < ESC_{rs}^{M}$	$ESC_{rs}^{N} > ESC_{rs}^{M}$	$ESC_{rs}^{N} < ESC_{rs}^{M}$
$\ln(\widehat{MR}_{rs,t})$	0.002	-0.003	-0.037	0.003	0.033	-0.005
	(0.068)	(0.011)	(0.086)	(0.016)	(0.115)	(0.015)
LS	-0.104	-0.381***	-0.072	-0.430***	-0.082	-0.325***
	(0.142)	(0.038)	(0.180)	(0.055)	(0.238)	(0.057)
$\ln(\widehat{MR}_{rs,t}) \times LS$	0.047	-0.030***	0.058	-0.040***	0.046	-0.022
	(0.043)	(0.009)	(0.054)	(0.013)	(0.073)	(0.014)
Observations	13,786	56,771	8,534	32,318	5,252	24,453
Adjusted R-squared	0.213	0.304	0.216	0.313	0.204	0.291

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample is restricted to natives between 15 and 65 years old. The control variables of the estimation are years of schooling, potential experience and its square, a dummy of women (in the full sample), and region and sector fixed effects. Regional expansion factors are used as weights. Odd columns are estimates from a sample restricted to those cells which the mean years of education of the immigrants there are lower to the mean years of education of the natives workers ($ESC_{rs}^{N} > ESC_{rs}^{M}$); even columns are restricted to the opposite subsample ($ESC_{rs}^{N} < ESC_{rs}^{M}$). Data are taken from the 2017 CASEN Survey.

In sum, the results shown in Table 6 are consistent with the downgrading effect, as recent migratory inflows have brought to Chile immigrant workers with more years of education than natives and who have taken up positions requiring lower qualifications than those that they occupied in their countries of origin. This phenomenon has had an influence on the salaries of the less qualified natives relative to the more qualified ones, since the competition for these jobs is now more intense.

5 Conclusion

During the 2015-2017 period, Chile received a record number of immigrants. The size of this inflow relative to the (comparatively small) native population makes it possible to identify the effects of migratory flows on the salaries of native workers.

Using information from the 2013-2017 CASEN surveys and data from the 2017 and 2002 population census, this paper shows that the mass inflow of migrants into Chile led to a 2-3% reduction in the salaries of low-skilled native workers who compete with more educated immigrants, suggesting a downgrading effect driven the results. This effect, which was mostly observed in 2017, derived from the great heterogeneity of the distribution of migrants across Chile's regions and economic sectors. The results obtained are robust to the use of instrumental variables. Multiple robustness tests validate the empirical strategy used.

These results are consistent with a number of qualitative studies that indicate an increase in the perceived threat reported by native workers, especially less qualified ones. Consequently, as in societies with long-standing immigration phenomena, xenophobic demonstrations and anti-immigration policies have entered the public debate. This situation is exemplified by recent migratory policies that increase restrictions for entering the country.

Although this article documents several negative effects of mass migration processes, these results must be interpreted in context. To start with, it is uncommon to observe a mass migration process such as that which took place in Chile for at least two reasons. First, it is unlikely for political-social processes such as those experienced by Venezuela or Haiti to occur systematically in the region. Second, the negative effects observed in 2017 are also partially explained by the weaker economic growth of the Chilean economy during that year. In other words, there was a mismatch between migrants' expectations (mass inflow) and the growth opportunities offered by the country. In a context of faster growth, it would have been less probable to observe such an impact.

This study does not identify any benefits associated with immigration. However, it can be hypothesised that greater competitiveness in the labour market should increase productivity in the long run. Another potentially beneficial feature of the immigration phenomenon is that Venezuelan migrants have a higher educational level than Chilean natives. Finally, it should be noted that a country like Chile needs to examine the migratory policies adopted by more developed countries, as this will make it possible to delineate inclusion and assimilation measures aimed at immigrants.

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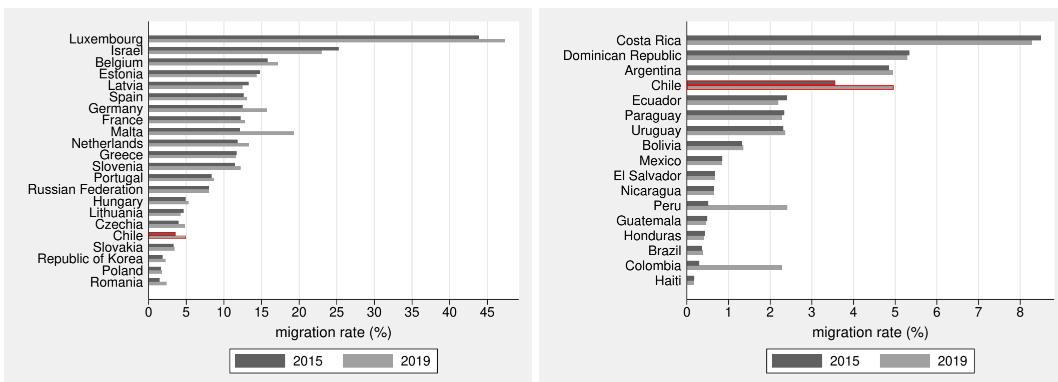
6 Appendix

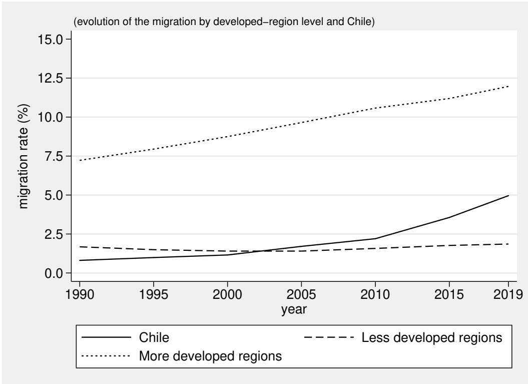
Figure 3: Migration rates in OECD and LAC countries (2015,2019).



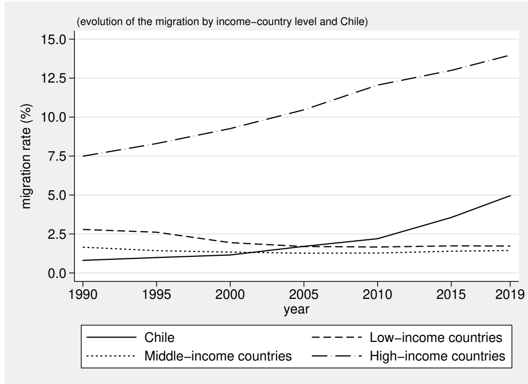
(a) OECD (b) LAC

Source: Own work based on United Nations data (Department of Economic and Social Affairs, Population Division, 2019).

Figure 4: Evolution of migration rates (1990-2019) by developed region level and income country level



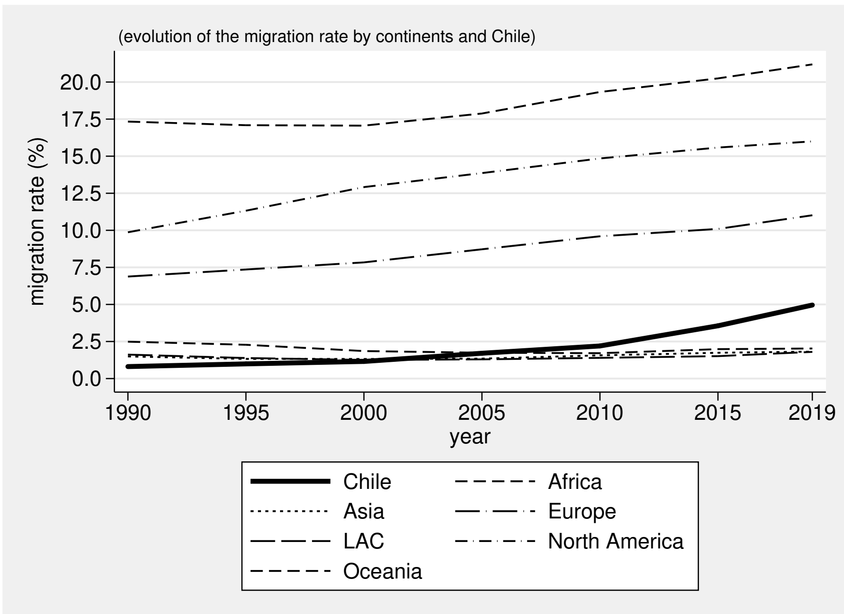
(a) Chile and less /more developed regions.



(b) Chile and low/middle/high income countries.

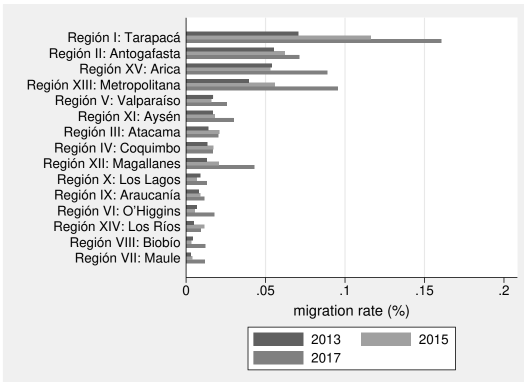
Source: Own work based on United Nations data (Department of Economic and Social Affairs, Population Division, 2019).

Figure 5: Evolution of migration rates (1990-2019) by continent.

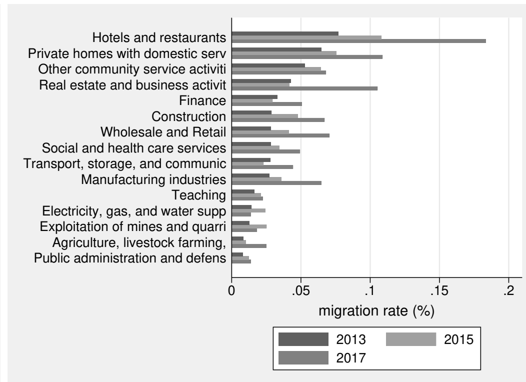


Source: Own work based on United Nations data (Department of Economic and Social Affairs, Population Division, 2019).

Figure 6: Migration rates in region and economic sector (2013,2017).



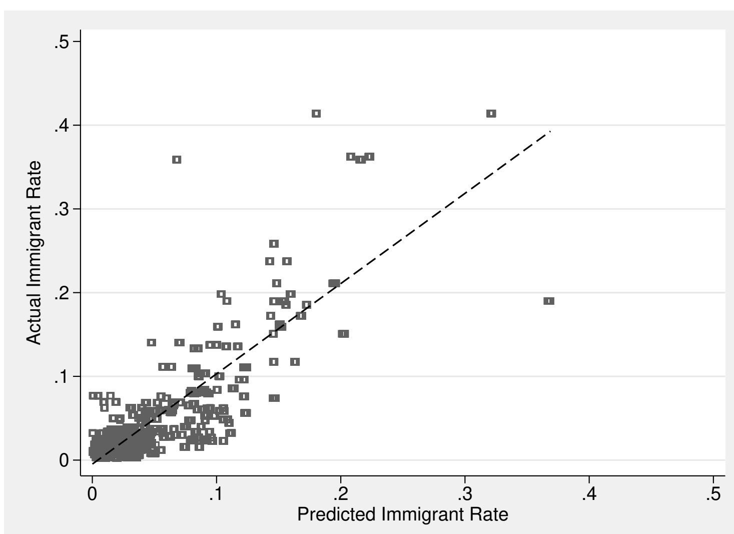
(a) By region



(b) By economic sector

Source: Own calculation using 2013, 2015, and 2017 CASEN survey waves. Expansion Factors at regional level are used as weights. Fractions are calculated considering the entire population in employment between 15 and 65 years old.

Figure 7: Current and supply-driven immigrant rates in region-sector cells.



Source: Own calculation based on 2017 CASEN survey and 2002 Census.

Table 7: Lagged mean log hourly wage and change in share of migrants.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Change in the share of migrants, 2013 to 2015			Change in the share of migrants, 2013 to 2017		
Panel A: *Current shares of migrants*						
Mean hourly wage in 2011	0.002	-0.006	0.003	-0.004	-0.001	-0.064
	(0.008)	(0.013)	(0.021)	(0.004)	(0.005)	(0.048)
Observations	240	240	228	240	240	228
Adjusted R-squared	-0.004	0.110	0.673	-0.003	0.004	0.321
Panel B: *Predicted shares of migrants*						
Mean hourly wage in 2011	-0.014	0.028	0.001	-0.013**	-0.007	-0.046
	(0.020)	(0.035)	(0.016)	(0.007)	(0.015)	(0.056)
Observations	228	228	228	228	228	228
Adjusted R-squared	0.000	0.252	0.549	0.001	0.093	0.378
Controls	No	Yes	Yes	No	Yes	Yes
Region and Sector FE	No	No	Yes	No	Yes	Yes

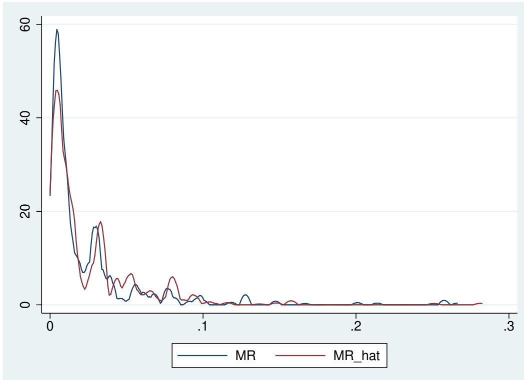
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The control variables of the estimation are years of schooling, potential experience and its square, and region and sector fixed effects. Regional expansion factors are used as weights.

Table 8: Correlation of the instruments with pre/contemporary trends of hourly wages

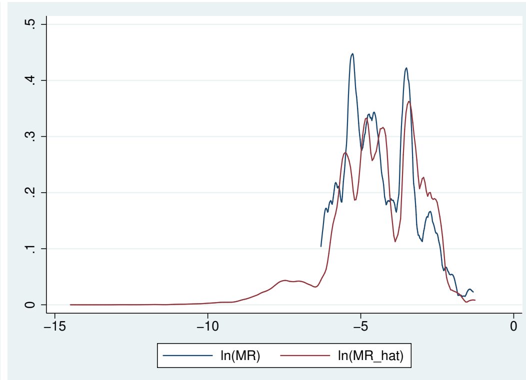
VARIABLES	Change in predicted share of migrants between 2015 and 2017		
	(1)	(2)	(3)
Panel A: *Pre-trend correlations*			
Change in log hourly wage (2011-2013)	0.015	0.015	-0.007
	(0.044)	(0.043)	(0.005)
Observations	227	227	227
Adjusted R-squared	-0.001	-0.002	0.972
Panel B: *Contemporary-trend correlations*			
Change in log hourly wage (2015-2017)	-0.039	-0.060	-0.008
	(0.035)	(0.044)	(0.006)
Observations	227	227	227
Adjusted R-squared	0.006	0.191	0.319
Controls	No	Yes	Yes
Region and Sector FE	No	No	Yes

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The control variables of the estimation are years of schooling, potential experience and its square, and region and sector fixed effects. Regional expansion factors are used as weights.

Figure 8: predicted and actual migrations rates (2013)



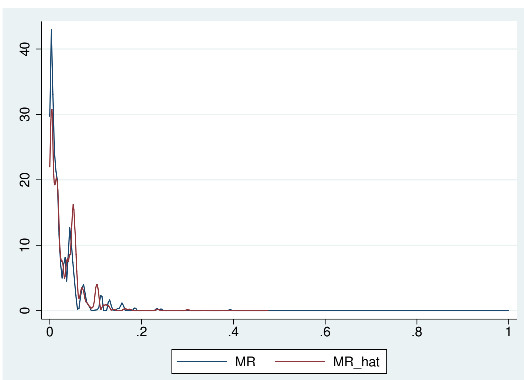
(a) rate



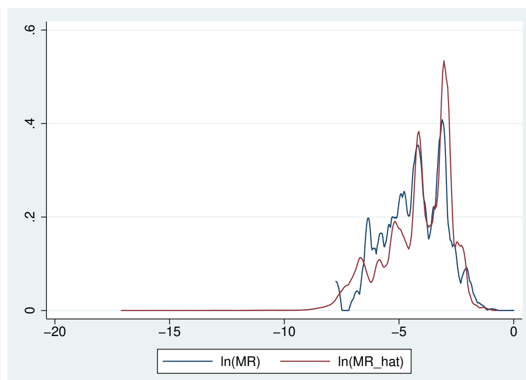
(b) logs

Note: Immigration rates are calculated at the level of region-sector cells using data from the 2013 CASEN survey (in blue); predicted rates (in red) are calculated in the first stage defined in equation (2) of this paper.

Figure 9: predicted and actual migrations rates (2015)



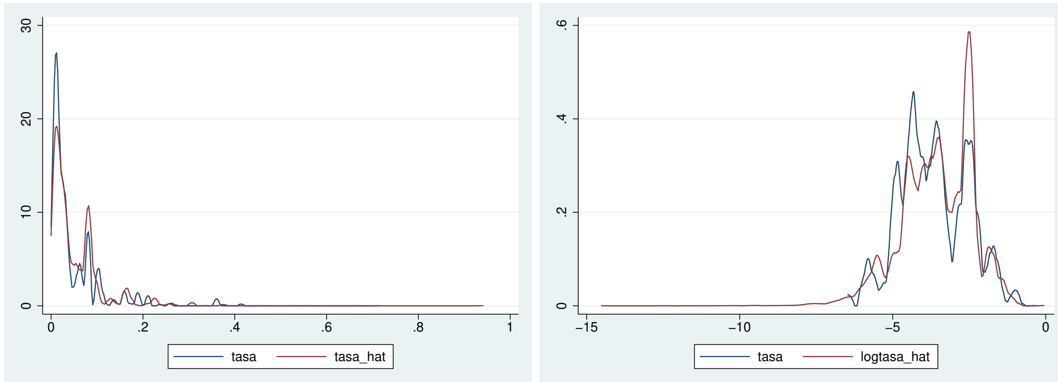
(a) rate



(b) logs

Note: Immigration rates are calculated at the level of region-sector cells using data from the 2015 CASEN survey (in blue); predicted rates (in red) are calculated in the first stage defined in equation (2) of this paper.

Figure 10: predicted and actual migrations rates (2017)



(a) rate (b) logs

Note: Immigration rates are calculated at the level of region-sector cells using data from the 2017 CASEN survey (in blue); predicted rates (in red) are calculated in the first stage defined in equation (2) of this paper.

Table 9: Effects of region-sector share of migrants on log wages of native workers (2SLS - Instrument for total population).

		2013			2015			2017	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Full	Men	Women	Full	Men	Women	Full	Men	Women
Panel A: Second Stage									
$\ln(\widehat{MR}_{rs,t})$	-0.005	0.015	-0.027**	-0.006	0.007	-0.017	0.021***	0.017*	0.030***
	(0.010)	(0.014)	(0.013)	(0.008)	(0.012)	(0.011)	(0.006)	(0.010)	(0.009)
LS	-0.388***	-0.501***	-0.251***	-0.326***	-0.391***	-0.262***	-0.351***	-0.405***	-0.297***
	(0.038)	(0.056)	(0.051)	(0.027)	(0.039)	(0.038)	(0.027)	(0.039)	(0.038)
$\ln(\widehat{MR}_{rs,t}) \times LS$	-0.017**	-0.036***	0.003	-0.007	-0.018*	-0.000	-0.022***	-0.034***	-0.014
	(0.008)	(0.012)	(0.011)	(0.006)	(0.009)	(0.008)	(0.007)	(0.010)	(0.009)
Observations	72,218	44,040	28,178	86,134	51,453	34,681	72,117	41,945	30,172
Adjusted R-squared	0.312	0.320	0.299	0.309	0.319	0.282	0.294	0.300	0.284
Panel B: Total Effect	-0.017**	-0.012	-0.025**	-0.011	-0.006	-0.018**	0.006	-0.007	0.021**
	(0.008)	(0.013)	(0.010)	(0.006)	(0.008)	(0.008)	(0.006)	(0.009)	(0.008)
Panel C: First Stage									
$Z_{rs,t}$		0.446***			0.374***			0.402***	
		(0.015)			(0.010)			(0.009)	
$Z_{rs,t} \times LS$		0.027**			0.053***			0.067***	
		(0.013)			(0.007)			(0.006)	
Total effect		0.466***			0.411***			0.446***	
		(0.007)			(0.007)			(0.005)	
Observations		81,932							
Adjusted R-squared		0.847							
F-test $Z^1_{rs,t}$		836.86			1350.44			1649.91	
F-test $Z^1_{rs,t} + Z^1_{rs,t} \times LS$		4857.64			1788.66			14292.67	

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample is restricted to natives between 15 and 65 years old. The control variables of the estimation are years of schooling, potential experience and its square, a dummy of women (in the full sample), and region and sector fixed effects. Regional expansion factors are used as weights.