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"Inmigración y Segregación en Chile: Evidencia para un Grupo Heterogeneo"

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Immigration and Segregation in Chile: Evidence for a Heterogeneous Group

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Abstract

This paper surveys migratory and ethnic wage gaps in Chile using a non-parametric alternative to the traditional Oaxaca-Blinder Decomposition, developed by Ñopo (2008). It is found that in general, immigrants tend to do better in labour markets, earning on average more than native workers in both 2015 and 2017. However, immigrants are a heterogeneous group, and when heterogeneities are taken into account, most of the relationships found disappear. This is particularly strong for those from countries with high Afro-descendant or Hispanic population, who earn on average -16% than natives in 2017, and in general are subject higher (negative) unexplained pay gaps in the same year. Moreover, similar results can be found for immigrants with 5 or less years of residence -as can be expected- and for those who are located in the North of Chile. Also, this paper provides evidence of occupational segregation among immigrants of the high African/Hispanic group with five or more years of residence, who appears to be subjected to a "glass ceiling effect".

JEL Codes: J15, J16, J71, F22.

Highlights

- Wages of immigrants declined between 2015 and 2017.
- Heterogeneities are important. Taking them into account improves the analysis.
- Immigrants from countries with high African/Hispanic ascendancy face negative unobserved gaps.
- Occupational segregation may be only directed towards certain subgroups.

Contents

1 Introduction

"Migration is the oldest action against poverty " [J.K Galbraith (1980)]

Immigration in Chile has become a topic in vogue in recent years and the unprecedented magnitude in which it has manifested itself determines it as a relevant phenomenon on a national scale. This fact has generated polarized positions at the local level. On the one hand, there are those who conceive immigration as an importation of poverty; they argue that immigrants take jobs, bring crime, provoke wage decreases and that most of the income they generate disappears in the form of remittances. In contrast, others argue that these claims are not true, advocating fair and equal treatment of foreign citizens.

In fact, in recent years, various immigrant associations have held marches against racism and discrimination in the workplace. In addition, a survey conducted by the National Center for Migration Studies at the University of Talca found that an average of 58.1 percent of migrants believe that people coming from their same country have more difficulty finding employment than foreigners of another nationality. These trends are especially marked for immigrants from countries with a high Afro-descendant population, since, for example, 82.6% of Haitians surveyed perceive greater difficulties.

Toward the year 2018 the opinion of Chileans regarding immigrants had hardened. This was revealed by the results of the 2018 Bicentennial Survey, conducted by the Catholic University and Gfk Adimark, between July and August 2018. According to the report, 50% of Chileans are in favour of the expulsion of immigrants who entered the country irregularly. Likewise, 75% of those surveyed considered the number of foreigners in Chile to be "excessive", and 62% believed that the inflow of migrants should decrease. As for the country's economy, 41% disagreed that "immigrants have done well to it" and 35% said that "foreigners limit Chileans" ability to find work.

Another study, the CADEM survey conducted in 2019 reflected that, in global terms, Chileans support a restrictive policy to face the migratory phenomenon in our country, since 83% of those surveyed answer that there should be entry requirements, while only 15% endorse an open door policy. In fact, 72% of the sample say that the number of immigrants currently in Chile is "high or excessive,".

What's more, 44% of those surveyed believe that the arrival of immigrants is negative for the country.

These facts are suggestive of the existence of some kind segregation/discrimination against immigrant groups in the labour market. An important type is manifested through wages; a situation in which an employer pays different wages to two practically identical individuals who differ in a characteristic with no direct effect on their productivity. Understanding that wages are in general a significant variable in people's well-being, it will be studied whether certain immigrant worker groups are subject to unexplained wage differentials, the possible mechanisms behind this phenomena and its evolution through the last years.

Discrimination against immigrants does not necessarily translate into wage gaps vis-à-vis native workers and can take multiple forms. However, if unexplained gaps are found they must be heterogeneous, since they are determined by different factors such as socio-economic status, gender, nationality, ethnicity, or some combination of these. For this reason the exercise will be carried out in consideration of some of the heterogeneities within this group.

In relation to the above statements, there seems to be a deep-seated perception among Chileans that discrimination against them exists and is a substantial factor in their search for job opportunities. According to a survey carried in 2018 out by the *Servicio Jesuita a Migrantes* to a sample of of middle class chileans[1], revealed that they considered the color of skin as a key factor for their success.

Despite this perceptions, economic literature reported or had demonstrated a plethora of benefits associated to immigration, specially to high skilled immigration. Borjas (1995) argued that, as long as there are no externalities, an application of the fundamental theorems of welfare economics and the principles of free trade suggests that allowing factors of production -as labour in the form of immigrant inflows- to move from one country to another increases total welfare and efficiency. However this is done with the caveat that the discussion ignores some very important issues. For example, by focusing on the economic benefits accruing to natives residing in the host country, the study ignores the impact of immigration both on the immigrants themselves and on the persons who remain in the source coun-

[1] In particular, to develop the study, a sample of non-probabilistic type was selected, of 871 cases of men and women resident in Santiago and regions, belonging to the socioeconomic segments C1, C2 and C3.

tries. Similarly, by focusing on a competitive economy with market-clearing and full employment, the analysis ignores the potentially harmful effects of immigration when there is structural unemployment in the host economy, and jobs might be a "prize" that are captured partly by immigrants.

Jaimovich and Siu (2017) studied the role of high-skilled immigration in accounting for changes in the occupational-skill distribution and wage inequality. They do so in a general equilibrium model featuring endogenous non-routine-biased technical change, using it to quantify the impact of high-skilled immigration and the increasing tendency of the foreign-born to work in innovation on, the pace of technical change, the polarization of employment opportunities, and the evolution of wage inequality since 1980 in the U.S. Particularly they find that high-skilled immigration has led to a narrowing of inequality.

For its part Agrawal et al (2018) in an attempt to better identify the benefits of high-skilled immigration, concerned by the possibility that local knowledge networks can be disrupted by arrivals that displace domestic workers who are better embedded in knowledge-sharing networks, use citation patterns to answer if immigrant scientists are less connected to the US scientific community than the domestic scientists they displace. They find that although immigrant scientists are significantly less connected than their domestic peers pre-immigration, convergence is rapid post-immigration. Overall, they do not find evidence of harm to domestic science through a knowledge network disruption channel. In fact there's important evidence regarding that high-skill migrants are strongly associated with higher patenting activity (Kerr and Lincoln, 2013; Hunt and Gauthier-Loiselle, 2010; Khana and Lee, 2018).

In the local context Pedemonte and Undurraga (2019) reported that in 2017 immigrants contributed 680.2 billion pesos to GDP through taxes, which represents 0.38 percent of the total. In addition Maire Chávez (2019) showed that in 2018 that foreigners who pay taxes in Chile, paid 3.2 times more than Chileans. Also, it was revealed by the Chilean Internal Revenue Service that foreigners not only increased in the number of taxpayers with declared income, but also, the total amount collected from this group increased in the last years.

Having all of this in consideration, the importance of this study lies first and foremost in considerations of human rights and retributive justice, understanding that discrimination can lead to occupational segregation of migrants and the generation of multiple inequalities [2], with harmful effects on their well-being. In fact, it has been reported in other countries that several immigrants tend to engage in activities that are rejected by native workers and if they compete with native workers, they do so for lower wages or under more precarious conditions.

In addition, wage discrimination causes - at least for a certain period of time - economic inefficiencies through misallocation of resources, by preventing the equalization of wages and marginal productivities in the disadvantaged group. It can also generate incentives for occupational segregation (Becker, 1957; Goldin, 2014), and in this sense, Pareto's optimum would be achieved only through a complete segmentation of the labour market, an aspect that seems to deeply elude the reality we observe.

Milgrom and Oster (1987), in turn, argue that companies benefit by hiding talented workers from the discriminated group in low-level jobs. As a result, these workers are paid less on average and promoted less often than others with the same education and skills[3]. As a result of discriminatory inefficient wage and promotion policies, workers in the disadvantaged group experience lower returns on their investments in human capital compared to other workers, and thus will be less productive, even though they are equally skilled. In this sense, there is a socially inefficient loss of talents.

Finally, the evidence on the existence of negative wage differentials against migrants in Chile is quite scarce, so this study will try to add more information on that presented in Contreras et al (2013), considering that immigration proceeds at a much more intense pace than in the period considered by the study since -for example- 67% of immigrants resident in the country, have arrived after 2010.

2 Theoretical Framework

In economics there are two major models of wage discrimination in labour markets: Statistical Discrimination (Phelps, 1972; Arrow, 1973) and Taste Discrimination (Becker, 1957). The former allows immigrants and natives to differ in their average productivity due to unobservable causes, but employers will use ethnicity or nationality as an approximation to it, which would also be reflected in

[2] Aside from income inequality, other dimensions, such as health, education, housing and other social services, must also be considered

[3] This theory is known as "Invisibility Hypothesis"

lower wages (Autor 2003). For its part, the latter, considers three sources for discrimination, employer, worker and customer.

The first source assumes that the employer has some prejudice that makes him hold a “taste for discrimination”, meaning that there is a disamenity value to employing minority workers. Hence, minority workers may have to ‘compensate’ employers by being more productive at a given wage or, equivalently, by accepting a lower wage for identical productivity in hiring immigrants. Then, regardless of their productivity, this displeasure will be reflected in lower wages for this group.

For worker discrimination assume that some members of the majority group are prejudiced against minority workers and demand a premium to work alongside them. This is similar to the case above, and leads to segregation. In the spirit of this paper this means that natives would demand a premium to work alongside immigrants.

Similarly, the model also takes into account customer discrimination. Assume instead that customers discriminate against minority workers and so get lower utility from purchasing services from a firm if they have to interact with these workers. This will lower their labour market return if they work in jobs with customer contact. In this case, it is not clear that consumer discrimination will be competed away by the market. This is because there is not an obvious way for one consumer to arbitrage the prejudice of another (Autor, 2003). Hence, this model suggests that customer prejudice may actually present a more enduring source of labour market discrimination than employer prejudice.

To illustrate employer discrimination model is used. Assume that there are two types of workers, which can be denoted by A for the majority group and B for the minority group. Employers will choose the quantity of labour L_X with $X = \{A, B\}$ of each type of worker that maximize their utility. So the optimal number of hired employees from each group is determined by the solutions to the following F.O.C:

$$\begin{aligned} pF'(L_A) &= w_A \\ pF'(L_B) &= w_B + d \end{aligned} \tag{1}$$

Where d is the coefficient of discrimination. Employers who are prejudiced will act as if the wage of group B members is $w_b + d$ and will hire group B workers if and only if $w_a - w_b > 0$. A wage differential will arise if the fraction of discriminatory employers is large enough for the demand for B workers when $w_A = w_B$ being lower than the supply. Some members of the B group will work with employers of the $d > 0$ type, and this will mean that $w_A > w_B$.

In competitive markets, without entry barriers or constant returns to scale, these employers wont be competitive and will have to exit the market, as each worker must be paid according to the value of their marginal product. In this scenario, non-discriminatory firms will simply expand to arbitrate the wage differential of workers from disadvantaged groups. This of course presupposes that there are enough non-discriminatory employers in these markets.

Under partial equilibrium, minority workers must "compensate" biased employers by being more productive at a given wage or, equivalently, by accepting a lower wage than the rest of the workers, for any level of productivity (Autor, 2003). These tastes create incentives for job segregation. For minority workers, it is potentially optimal in the sense of Pareto to work in their own businesses and for majority workers the logic will be equivalent. In this way no one has to bear the cost of the displeasure.

Consequently a first testable implication in the context of this work is the existence of wage gaps and the subsequent analysis of their composition. Then, whether w the salary of an individual i, the general formulation of the problem could be posed through the following estimable equation:

$$ln(w_i) = \beta_0 + \beta_1 M_i + \gamma X_i + \varepsilon_i \tag{2}$$

Where X_i is a vector of exogenous characteristics related to the productivity of i and M_i is a binary variable equal to 1 if the individual is a immigrant and equal to 0 if not, while ε_i corresponds to an error term. In this case the coefficient β_1 gives us the log-salary differential between immigrants and natives. Assuming that γX_i fully captures the set of characteristics and their returns and M_i is not correlated with ε_i, then a negative gap -perhaps attributable to discrimination- will emerge in a case where $\beta_1 < 0$.

Other testable implications of the Becker model relate to the verification of the emergence sectoral or occupational segregation, in the sense that workers should be concentrated in the sectors, occupations, geographical areas or labour markets where they are not discriminated against in terms of their wage or are most valued for their specific skills. In this sense one should expect to see under representation of the minority workers in those sectors/occupations where negative wage differentials arises.

However, the estimation of (2) presents some complications. For example, even X_i could be endogenous in the sense that discrimination could appear before entering the labour market, maybe because of expectations of future discrimination[4], reducing X_i for members of the minority group.

In the spirit of this work, as we are treating with immigrants, there are other sources of potential identification problems of the true gap between groups. One comes from the fact that immigrants are not a random sample of the population of their countries of origin in the sense that there are factors that motivate only some types of people to migrate to the host country, so self-selection in the influx of immigrants has the potential to bias the estimation of the parameter of interest.

Borjas (1987, 1994, 1999) provides a theoretical approach to the resolution of this question, taking Roy's model (Roy, 1951) as the basis for this formulation. In a set-up of two countries, denoted by 0 and 1, the model highlights the importance of differences in skills between migrants and natives at the time of making the decision. Workers will find attractive to migrate only if the benefits of migration in terms of wages, surpasses their costs[5]. It can be shown in this set-up that average wages of those who migrate in the source (counterfactual) and host country are:

$$E\left[w_0 \middle| Immigrant\right] = \mu_0 + \frac{\sigma_0\sigma_1}{\sigma_\nu}\left(\rho - \frac{\sigma_0}{\sigma_1}\right)\left(\frac{\phi(z)}{1-\Phi(z)}\right) \tag{3}$$

$$E\left[w_1 \middle| Immigrant\right] = \mu_1 + \frac{\sigma_0\sigma_1}{\sigma_\nu}\left(\frac{\sigma_1}{\sigma_0} - \rho\right)\left(\frac{\phi(z)}{1-\Phi(z)}\right) \tag{4}$$

Where μ_0 and μ_1 are the mean wages in the source and host country respectively, ρ is the corre-

[4]This would go according to what Milgrom and Oster (1987) stated, for example, lower expected returns to education will lead to lower investment in human capital.

[5]These involve direct costs (e.g., transport of people and goods), costs in the form of foregone opportunities (e.g., the opportunity cost of income foregone through migration) and psychological costs (e.g., the disutility associated with leaving behind family ties and social networks)

lation of skills in both countries, σ_0 and σ_1 are the returns to skills in the source and host country and the rightmost term is the inverse Mills ratio for those who migrate. In this way, 3 cases of selection of immigrants can be identified:

i) Immigrants are positively selected from the distribution of the country of origin and are also above the average of the distribution of the host country. This will be true if and only if:

$$\frac{\sigma_1}{\sigma_0} > 1 \text{ and } \rho > \frac{\sigma_0}{\sigma_1}$$

From this it follows first that $\sigma_1 > 0$ and $\sigma_0 > 0$ imply that the host country has greater returns to skill than the country of origin. Second, $\rho > \sigma_0/\sigma_1$, implies that the correlation between the skills assessed in the host and in the home country is high enough. In this case a skilled worker in the country of origin would not find it convenient to migrate to a host country with a high return to skills if the skills valued in the host country were not correlated (or negatively correlated) with the value of the skills in the country of origin.

ii) Another case is where immigrants are negatively selected from the distribution of the country of origin and are also below the average distribution of the host country:

$$\frac{\sigma_0}{\sigma_1} > 1 \text{ and } \rho > \frac{\sigma_1}{\sigma_0}$$

This is simply the opposite of i). The country of origin is not attractive to low-income workers because of the high wage dispersion. Again assuming that wages are sufficiently correlated between the country of origin and the host country, low-skilled workers will want to migrate to take advantage of the "insurance" provided by a more compressed salary structure in the host country. From the perspective of Borjas (1987) this is a potentially unattractive case, where the compressed wage structure subsidizes low-skilled workers, and consequently it is this class of workers who are attracted to the decision to migrate.

iii) A third case is when immigrants are selected from the bottom tail of the distribution of the country of origin, but arrive at the top tail of the distribution of the host country. This can only happen if and only if:

$$\rho < min\left(\frac{\sigma_0}{\sigma_1}, \frac{\sigma_1}{\sigma_0}\right)$$

This means that the correlation between the gains in the two countries is sufficiently low (it could even be negative). This could happen, for example, if the set of skills valued in the home country differs substantially from that in the host country.

This analysis also can be extended to he case where selection is on observable skills like schooling. Suppose a worker gets s years of schooling before making the decision to migrate, and that this educational achievement can be observed and valued by employers in both countries. Then the average schooling of immigrants will be lower or higher than the average schooling in the country of origin depending on which country has higher returns to education. Thus, the most educated workers will end up in the country that values them the most.

The fact that factors such as returns to education may determine the type of immigration to which the country will be subject means that a priori it is not possible to elucidate the situation of immigrant workers in relative terms with respect to their native counterpart. In fact, it may well be that different types of selection operate for different geographical areas or different economic sectors. For this reason, an exercise aimed at verifying their relative situation, apart from explicitly taking into account the problem of selection, should also explore the consequences of these potential sources of heterogeneity among the immigrant population.

Also, the estimation of (2) also presents some limitations when taking into account other heterogeneities present in discrimination suspect group. For example, one potential source relates to the skills of migrants and how these change over time as they adapt to the labour market of the host country. So, wage gaps can emerge because of differences in the host country specific human capital. Thus, if the object of interest is the situation of immigrants in the labour market, it should be taken into account that this estimation may vary according to, for example, the length of stay of the immigrant in the host country and lack of assimilation of these specific skills could be attributed to unobservables or discrimination. Then a proper identification strategy must also account for this fact.

3 Literature Review

Starting with the seminal work of Chiswick 1978, most of the studies that try to assess the relative situation of immigrants compared to natives in the labour markets, have been carried out internationally. These have placed special emphasis on their relative wages, and most of their findings can be summarized in that immigrants generally face a significant gap in relation to native workers. These studies can be classified in three large classes; those that analyse the average wage gap, those that do it through the wage distribution and those that take into account problems that arise in the comparison of individuals with totally different characteristics.

It was not until the study of Borjas (1987) that potential identification problems associated with endogeneity in the decision to migrate were explicitly taken into account. In particular, using the theoretical framework provided by Roy (1951) to justify correction for selection bias, the author shows that in the United States the wage differentials between immigrants and natives with the same observable skills were attributable to variations in the in the political and economic conditions in their countries of origin at the time of migration.

Following this line, and incorporating decomposition methodologies, Kee (1995) found significant wage gaps between immigrants and natives in Netherlands (unfavourable to the first group), with great variations according to the worker's country of origin. The author attributes these differences to wage discrimination, however, the methodology used does not allow us to know for certain whether the estimated differences are attributable to discrimination per-se or to differences in the unobservable characteristics of workers.

Nielsen et al (2004) find similar results of those found by Kee (1995) but they perform their analysis for Denmark. The authors put emphasis in the fact that the returns to education are positive for the natives and this is generally not the case for immigrants. Particularly for women from Turkey, Pakistan and Africa these are negative.

For their part, Adsera and Chiswick (2007) used the 1994-2000 waves of the European Community Household Panel to study the wages of immigrants compared to native workers in 15 European countries. At the time of the foreigner's arrival, the authors find a negative and statistically significant effect on their individual incomes of around 40%. These differences vary between origins and destinations and also by gender, although they tend to disappear as immigrants increase their years of residence in the host country.

For the United States and Great Britain, using cross-sectional data repeated over time, Schmitt and Wadsworth (2007) study the relative performance of immigrants in the labour market during the period 1980-2000. Their results suggest that the average wage gap between immigrants and natives appears to have increased in both countries over time, with particular strength among non-Caucasian immigrants.

For its part Aldashev et al (2008) taking into account some heterogeneites found among immigrants analyses the wage differentials between native Germans and two immigrant groups: foreigners and naturalized immigrants. To do this they perform Oaxaca Blinder decompositions, finding that there is a considerable wage gap between immigrants and natives in Germany. Also, much of the gap is due to the fact that immigrants are paid less than natives for observationally equivalent characteristics.

Focusing only on Great Britain Brynin and Guveli (2012) points out that discrimination can occur at two points, at entry to the job and within the job. For example, in the former case non-whites might find it difficult to work in well-paid occupations; in the latter they obtain the same sorts of jobs as whites but receive less pay. Taking this into account the authors use the British Labour Force Survey 1993–2008 to show that much of the pay gap is explained by occupational segregation while within occupations the ethnic pay gap is far less substantial.

Also for Great Britain, Miranda and Zhu (2013) focus on the effect of English deficiency on the native-immigrant wage gap for employees in the UK using the first wave of the UK Household Longitudinal Survey (Understanding Society). They show that the wage gap is robust to controls for age, region of residence, educational attainment and ethnicity, particularly for men. However, English as Additional Language (EAL) is capable of explaining virtually all the remaining wage gap between natives and immigrants.

For Austria Hofer et al (2017), using data from the Austrian Labour Force Survey, report the existence of wage discrimination against immigrants. Also for Austria Christl et al (2018) using decomposition techniques and controlling for sample selection bias find that for both groups, literacy skills are an important determinant of the hourly wage. They then show that differences in proficiency with respect to literacy can explain more than three log points of the total wage gap of 9.7 log points between natives and immigrants. Furthermore when adding literacy skills to the wage decomposition, the discriminatory part vanishes completely, suggesting that the wage difference between immigrants and natives in Austria can be to a large extent explained.

Within the second group of studies, Butcher and DiNardo (2002) using non parametric density estimates, take into account the problem (at the time) of focusing only on males in calculating the wage gap between immigrants and natives. In particular the authors find that patterns of comparison between the wages of immigrants and the native-born are not the same for men and women. Also, while performing a counterfactual analysis they find that the wage distribution that results from the 1990 wage structure and the 1970 distribution of schooling, potential experience, geographic distribution, industry, race, ethnicity, country of origin, etc. is markedly similar to the wage distribution that prevailed for recent immigrants in 1990.

Lehmer and Ludsteck (2011) in a study conducted for Germany too, report the existence of of wage discrimination against immigrants from Eastern Europe through the use of quantile regressions and decomposition techniques. They find that that the magnitude of the gap varies along the income distribution, being more pronounced in the lower quantiles.Coppola et al (2013), investigate the wage gap between immigrants and Italian natives across the entire wage distribution. For this they use data from the Income Survey and Living Conditions of Households with Foreigners for the year 2009. They also consider additional sources of heterogeneity among immigrants, such as the length of their stay in Italy and their proficiency in the Italian language. Thus, the authors show the existence of a large wage gap between immigrants and natives, which increases throughout the distribution, suggesting the existence of a "glass ceiling effect[6]" for immigrant workers. They also find evidence of a continuous but largely incomplete assimilation process among the immigrant population, and a smaller gap for

[6]The glass ceiling is a metaphor referring to an artificial barrier that prevents women and minorities from being promoted to managerial- and executive-level positions within an organization

immigrants with greater mastery of the Italian language.

Billger and Lamarche (2015) use longitudinal data from the Panel Study of Income Dynamics (PSID) and British Household Panel Survey (BHPS) to examine wage differences among native immigrants across the distribution, controlling for individual heterogeneity. The authors use quantile regression techniques to estimate conditional quantile functions for longitudinal data. In show that country of origin and gender are determining factors in income differences between immigrants and natives.

Fortin et al (2016) trying to verify the role of foreign acquired human capital in the Canadian migratory wage gap, used a direct question, available in the 2006 Canadian census, regarding the location where the highest degree of education was attained. The identification of the human capital source explains up to 70% of the initial immigrant/native wage gap. They show that the separation of both the education and work experience into native and foreign sources are deciding factors in the reduction of the wage gap from around 11%-12% to close to 3% indicating that the Canadian labour market gives a negative wage premium to education and work experience acquired abroad. Also the incorporation of location of study fixed effects provides evidence that education obtained in Asia tends to be less valued than education obtained in South America, Africa and East Europe.

Within the final group, in a study conducted in Spain, Nicodemo and Ramos (2012), using matching strategies that take into account the problem of common support that arises when comparing individuals with different characteristics, show that immigrant women in Spain receive lower salaries than native women. In this sense it is ensured that the estimation of the gap is made between comparable people in their characteristics, attenuating potential selection problems. In addition, the authors conclude that immigrant women are subject to double discrimination, in the first instance because they are women, and in the second instance because of their country of origin. Anyhow, it is hard to assert that there is indeed discrimination, because wage differentials can arise for differences in unobservable characteristics.

Finally, in Chile, the only attempt to measure wage gaps between immigrants and natives found was conducted by Contreras et al (2013), whom, using data from the 2006 and 2009 CASEN surveys, show that, on average, immigrants earned higher wages than native-born workers during those years. The authors explicitly take into account the problem of selection arising from the non-randomness of immigration, and use Heckman's correction (1979) in their estimates.

4 Descriptive Statistics: A characterization of the Immigrants

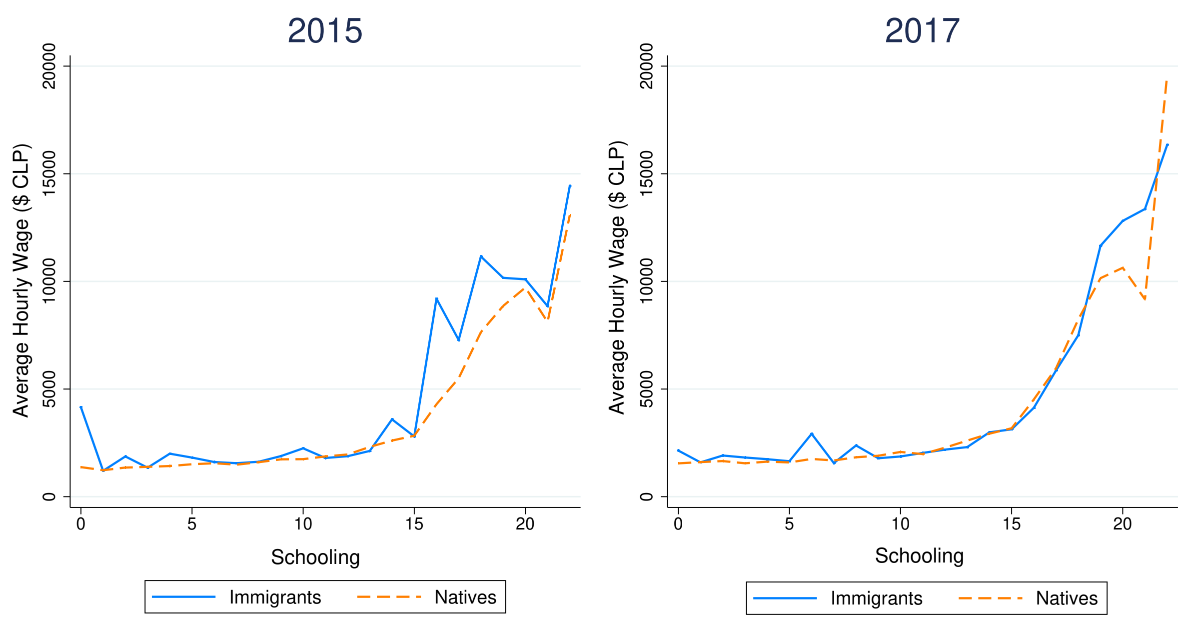
The main dataset used in this paper is the 2015 and 2017 waves of the Chilean National Socioeconomic Characterization Survey (CASEN). CASEN is a household survey applied by the Chilean Ministry of Social Development every two or three years. This survey is the main source for Chile's socio economic statistics, such as the official poverty rate, and its information is periodically used to assess the impact of social policies and programs. On average, CASEN includes survey information for about 65,000 households in 300 municipalities, around 1.5% of the national population. In this survey is possible to find, in addition to wages, numerous socio-economic and labour characteristics that the literature has shown to be relevant in wage determination; such as the schooling or educational level of the workers, their gender, age, occupation, economic sector, etc.

In the context of this study, all individuals that respond yes to the question "at the time of birth, was your mother outside of the country?" will be considered immigrants. This is the best approximation that can be found in the CASEN survey to whether the individual is indeed an immigrant. However, it also considers in this category those individuals who may well have developed most of their life in Chile, which in practice would make them more like a native worker, having enjoyed a greater window of time to obtain country-specific skills[7]. In addition, some limitations are recognized in the data sources because, in particular, this survey is not designed to study immigrants, so it may not capture the totality of them, even considering their associated weights. Also, informality (illegality) is inherent to a great part of them, so it is natural to suspect that they may be under-represented in both surveys.

Figure 1 shows a higher average hourly wage for working age immigrants[8] compared to its native counterpart during the year 2015, with larger differences for higher levels of schooling. However, in 2017 the magnitude of this difference is drastically reduced since it is observed to be more compressed

[7]This limitation will be taken into account later.
[8]The population aged 15 or over is considered

Figure 1: Hourly Wages Immigrants and Natives, by schooling, 2015 and 2017.



SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.

at almost all levels, giving some clues about a generalized deterioration in their situation.

Immigrants are then separated into two groups in order to verify whether there are substantial differences in their characteristics according to their racial origin or ancestry, as well as contrasting them with those of the native working-age population. For this purpose, we construct a group that contains the totality of the immigrants (Group 1) and another (Group 2) integrated by those coming from countries with a high percentage of Afro-descendant or Hispanic population [9]. From this, table 1 shows socio economic, demographic and labour characteristics of both immigrant groups and natives. It can be seen that by 2015, both groups have on average higher levels of schooling than natives, with 12.5 and 12.2 years versus 10.9 respectively, while the proportion of females reaches its highest value for group 2 (54.2%). Regarding the age dimension, it can be noted that the natives of working age are on average older than immigrants of both groups, with an average of 43.7 years versus 35.9 (Group 1) and 34.9 (Group 2). In the year 2017 the trend is similar, although it is possible to note that the gaps

[9] In year 2015 this category include immigrants from: Costa Rica, Cuba, Dominica, El Salvador, Guatemala, Haiti, Honduras, Mexico, Nicaragua, Panama, Dominican Republic, Bolivia, Brazil, Colombia, Ecuador, Paraguay, Peru and Venezuela. While in 2017 the list excludes Dominica and includes Ghana, Nigeria, Congo, South Africa, Uganda and Saint Kitts and Nevis.

Table 1: Characterization of Working Age Immigrants and Natives. 2015-2017.

	2015			**2017**		
	Group 1	**Group 2**	**Natives**	**Group 1**	**Group 2**	**Natives**
Age	35.9***	34.9***	43.7	35.2***	33.9***	44.8
Female (%)	53.4	54.2	53.6	52.3	52.9	53.5
Schooling	12.5***	12.2***	10.9	13.1***	12.9***	11.1
Income Poverty (%)	8.4	8.5	10.0	9.0	9.5	7.1
Multi-Dimensional Poverty (%)	21.5	25.3	18.2	22.3	24.8	17.6
Less than 5 years in Chile (%)	20.4	41.2	-	53.7	61.1	-
Employed (%)	72.4	75.3	53.4	75.3	77.2	53.8
Unenmployed (%)	4.4	3.9	4.4	6.0	6.2	4.6
Informal (%)	16.3	14.6	31.2	13.7	11.8	30.0
Weekly worked hours	44.6***	44.9***	42.8	44.5***	44.7 ***	42.4
Hourly Wage	3478***	3030***	2713	3315***	2617***	3126
Occupation (%)						
Managers	4.2	2.7	2.7	3.3	2.0	2.6
Professionals	8.7	6.4	6.3	8.7	6.5	6.7
Technicians and Associate Professionals	6.2	5.8	5.1	5.9	5.9	5.6
Clerical Support Workers	5.8	5.9	5.0	5.4	5.8	4.2
Services and Sale Workers	14.0	14.9	8.6	19.5	21.5	8.6
Skilled Agricultural, Forestry and Fishery Workers	1.1	1.3	2.5	0.8	0.9	1.9
Craft and Related Trades Workers	11.7	13.7	7.4	9.8	10.4	7.4
Plant and Machine Operators and Assemblers	3.0	3.0	4.9	2.9	2.9	4.8
Elementary Workers	17.5	21.6	10.8	11.7	21.2	18.8
Sector (%)						
Agriculture. Hunting and Forestry	1.6	1.6	4.8	2.5	2.6	4.6
Fishing	0.2	0.1	0.5	0.2	0.2	0.5
Mining and Quarrying	1.3	1.1	1.4	0.4	0.3	1.0
Manufacturing	6.4	6.9	5.1	7.0	7.3	5.0
Electricity, Gas and Water Supply	0.3	0.2	0.4	0.1	0.1	0.4
Construction	8.2	9.3	4.9	6.9	6.9	4.8
Wholesale and retail trade	15.0	15.8	10.3	16.3	17.7	10.6
Hotels and Restaurants	9.1	10.1	2.2	10.7	11.6	2.4
Transport, Storage and Communications	3.2	3.0	4.1	3.7	3.7	3.9
Financial Intermediation	1.0	0.9	1.0	0.9	0.7	0.9
Real estate, Renting and Business Activities	3.8	4.9	5.5	9.2	8.9	3.9
Public administration and defence; compulsory social security	1.2	1.0	2.8	0.8	0.4	0.8
Education	3.2	1.8	4.6	2.0	1.3	2.0
Health and Social Work	3.4	3.2	1.6	3.2	3.1	3.2
Other community, Social and Personal Service Activities	3.8	3.8	1.6	3.0	2.9	3.0
Private Households with Employed Persons	8.9	11.4	3.3	7.6	8.8	3.1
Observations	4236	2987	208494	5934	4707	169142

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.
* $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.
Differences in means for statistical significance are computed with respect to natives.

in schooling widen between immigrants and natives, while the migratory influxes of recent years have provided greater average youth to the population of both groups.

On the other hand, the percentage of occupation of both groups of immigrants is especially high, being about 20% higher than that of the native population in both periods mainly explained by a greater proportion of inactive people in the latter group. This responds to the fact that most of them are people who migrate in search of stable jobs and better wages (Borjas, 1987; Contreras et al, 2013; Felbermayr et al, 2015). The unemployment percentages of all groups during 2015 are more or less similar between Natives and Group 1 and stand at around 4.4% of the working-age population, while for group 2 it is only 3.9%. In 2017 these percentages increase strongly among the immigrant population, reaching 6.0% for group 1 and 6.2% for group 2.

Also, in 2015, about 20.4% of all working-age immigrants arrived in Chile less than 5 years ago, while 41.2% of the Group 2 stock arrived in the same period, demonstrating the great magnitude of the inflows (at least proportionally) to which the country has been subject in recent times. In fact, in 2017 the number of immigrants from both groups who arrived in the country in the last 5 years increased, with 53.7% of the stock of immigrant workers of group 1 and 61.1% of that of group 2, which is mainly explained by the enormous influx of Venezuelan and Haitian immigrants who arrived in the country between 2015 and 2017.

The table also shows that immigrants from both groups work nearly two hours more than their native counterparts in both periods. In addition, in 2015 they showed a higher average hourly wage than the Natives, with an absolute gap of 28.2% favourable to the first group and 11.6% for the second. In 2017 this gap is substantially reduced for group 1, going to 6.0%, while for group 2 it is reversed, going to -16.2%. One fact worth noting is how immigrants from countries other than Group 2 (mostly Caucasian) turn the gap positive, which tells us about the high wages they receive on average.

Although the hourly wages shown in table 1 reflect a better relative situation of immigrants (with the exception of Group 2 in 2017), an important part of this income is sent as remittances to family members abroad, so it should not be associated with a better standard of living, a fact reinforced by a higher proportion of immigrants - around 21.5% and 25.3% compared to 18.1% - appearing as multi-dimensionally poor in 2015, with similar proportions in 2017, indicating that their greater relative wealth does not translate into equal access to social services or housing.

With regard to their occupational concentration, it is possible to note in table **??** that their distribution in the different occupations (ISCO 1-digit classification) is more or less similar to that of the Natives and there are no differences of more than 5% between groups, although natives appear to be more concentrated in highly paid occupations (e.g Mangerial and Proffesionals). In line with the assimilation literature, this may indicate that several migrants have problems validating their studies[10] so, at least for some period of time since their arrival, they must work in sectors (at a higher level of disaggregation) other than their true profession, and probably in occupations that require a lower level of human capital than they already possess. Another reason can be that they face some kind of glass ceiling effect due to unobservable causes.

Finally, and in contrast to what can be observed regarding the concentration of both groups in the different occupations, their distribution across economic sectors (ISIC 1-digit classification) shows marked differences. There are six sectors where the proportion of immigrants from both groups is higher than that of natives, but they are especially marked in the sector *Hotels and Restaurants* and in the sector *Private Homes with Domestic Service*. On the other hand, in both periods, *Wholesale and Retail Trade* is the one that concentrates the highest proportion of workers from both groups, a percentage that has grown over the years. This suggests that this sector (perhaps together with the two mentioned above) is the one with easiest insertion for immigrant workers, probably arising from the use and exploitation of networks of the *bonding* type in the Lancee's (2012) terminology[11] , that is, those formed within the same group.

Geographically, at a general level, it is also possible to observe some interesting phenomena in table 2. For example, in both periods, immigrants are over-represented with respect to the native population both in the Great North (I, II and XV regions) and in the Metropolitan Region. In the opposite sense, Southern Chile is the area with the least representation. This pattern of settlement suggests two things:

- First of all immigrants tend to settle in areas close to their place of entry to the country, since a

[10]In fact, there is evidence for Chile regarding this assertion, which can be found in Lafortune and Tessada, (2016).

[11]Bonding refers to a dense network with thick trust and is measured as the strength of family ties and trust in the family. Bridging implies a crosscutting network with thin trust and is measured as inter-ethnic contacts and outward orientation (Lancee, 2012)

Table 2: Geographical Location by Region. Immigrants and Natives, 2015-2017.

Region (% of he total)	**2015**			**2017**		
	Group1 1	**Group 2**	**Natives**	**Group 1**	**Group 2**	**Natives**
I. Tarapacá	6.5	8.0	1.6	5.6	6.3	1.6
II. Antofagasta	6.2	7.6	3.1	4.4	4.5	3.1
III. Atacama	1.0	1.1	1.5	0.6	0.6	1.6
IV. Coquimbo	2.2	1.8	4.3	1.3	1.3	4.4
V. Valparaíso	5.1	2.5	10.7	5.0	3.6	10.9
VI. General Libertador Bernardo O'Higgins	0.9	0.6	5.3	1.7	1.6	5.5
VII. Maule	0.7	0.5	6.0	1.3	1.0	6.2
VIII. Biobío	1.2	0.7	12.3	2.2	1.8	9.6
IX. Araucanía	1.5	0.8	5.7	1.2	0.6	5.9
X. Los Lagos	1.0	0.5	5.0	1.2	0.8	5.2
XI. Aysén	0.3	0.2	0.6	0.3	0.2	0.6
XII. Magallanes	0.6	0.2	0.9	0.7	0.5	0.9
XIII. Metropolitana	70.2	73.1	39.9	71.8	74.8	38.8
XIV. Los Ríos	0.7	0.2	2.0	0.4	0.2	2.2
XV. Arica y Parinacota	1.7	2.2	0.9	1.6	1.8	0.8
XVI. Ñuble	-	-	-	0.5	0.4	2.7

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.

large part of Latin American immigrants[12] enter to Chile by land and they do so through border crossings in the North of the country.

- In second place, when observing the Great North in conjunction with the Metropolitan Region, and as reported in Contreras et al (2013) for the years 2006 and 2009, there is a tendency for immigrants to settle in locations with a large enclave of people from the same country, a fact that is presumably associated with the formation and exploitation of networks, understanding that these are an important consideration in the locating options for future immigrants, because they facilitate the process of employment search, the assimilation of the new culture and reduce risks and uncertainty (Card, 2001; Cortés, 2008).

Considering the fact that Chile is a diverse country, with important natural barriers (with effects on the mobility of workers) and geographically well-differentiated labour markets, it is illustrative to review the socio-demographic and labour characteristics of immigrants in the country's 4 large Geographic Zones, i.e., Greath North, Little North, Central Zone and South Zone [13]. This is done in consideration of the fact that these particularities -among others- could explain that the type of immi-

[12]These represent the vast majority of the migrant population in the country, for more details see Appendix

[13]Great North corresponds to the I, II and XV regions; Little North to III an IV; Central Zone to V, VI, VII, VIII, XIII and XVI; and South Zone to IX, X, XI, XII and XIV regions.

grants that arrive to different zones can differ substantially.

Table 3 show the reversal of some trends compared to the national average, especially in the Great North. In particular, although the proportion of females in each is more or less similar to that of males (slightly higher) and quite similar to that of the national average, in the Great North it can be seen as much higher in relative terms, given that females, in both periods, represent about 60% of the total population of migrants of working age in that area. Something similar happens with schooling levels; while in the rest of Chile immigrants exhibit higher levels, in the Great North the opposite is true. In 2015, group 1 averaged 11.2 years of schooling while Group 2 averaged 11.0 compared to 11.7 for natives. On the other hand, in 2017 the differences are similar, although the educational levels of all the groups were reduced between 0.2 and 0.3 years.

Also in the Great North it can be seen in table 3 that the trends in most of the other variables considered are similar to those of the rest of the country, however, both groups face a significant (and negative) wage gap with respect to the natives, of the order of -27.6% and -45.8% for groups 1 and 2 in 2015 and -16.3% and -61.4% in 2017 respectively. As for the levels of income poverty and multidimensional poverty, the differences are even more marked than at the country level in both years, with a deterioration in the relative situation of both groups of immigrants with respect to their native counterparts between 2015 and 2017, although at the same time there is also a substantial decrease in their levels of unemployment.

On the other hand, in the South, the wage gap in 2015 was favourable to immigrants and of great magnitude (36.3%), a fact that suggests that considering the greater distance in comparison to the other zones, those who travelled there, did so because of really attractive job opportunities. In fact, for the same year, immigrants from the second group have a 136.4% gap in their favour, which reaffirms the idea just exposed. However, in 2017 as more immigrants settled there, the situation changes radically. While group 1 received on average hourly wages similar to those of the natives (slightly higher), group 2 received on average lower wages than the latter, with an absolute gap of -2.0%.

This is indicative that at the moment of observing averages, the Central Zone carries all the weight.

Table 3: Characterization of Working Age Immigrants and Natives by Geographical Zone, 2015 and 2017.

Year	Variable	Great North			Little North			Central Zone			South Zone		
		Group 1	Group 2	Natives	Group 1	Group 2	Natives	Group 1	Group 2	Natives	Group 1	Group 2	Natives
2015	Age	35.3	34.8	42.3	36.9	35.7	44.3	34.9	33.7	44.8	37.9	34.4	45.6
	Female (%)	56.3	57.7	51.9	50.5	50.3	53.4	51.6	52.2	53.7	54.2	53.2	53.0
	Schooling	11.2	11.0	11.7	12.0	11.9	10.7	13.4	13.2	11.3	12.3	12.3	10.2
	Income Poverty (%)	12.7	13.4	4.2	15.3	15.6	8.9	8.4	8.9	6.1	8.1	7.6	12.0
	Multi-Dimensional Poverty (%)	33.1	35.5	16.8	21.5	19.4	19.4	21.2	23.5	16.5	16.9	20.2	21.8
	Less than 5 years in Chile (%)	3.4	3.6	-	13.1	18.1	-	21.3	26.7	-	45.4	71.4	-
	Employed (%)	72.5	72.1	53.7	69.7	72.8	47.9	76.2	78.1	54.8	68.9	78.1	51.3
	Unemployed (%)	2.8	2.8	5.1	6.5	7.9	5.6	6.5	6.8	4.6	5.4	6.4	4.0
	Informal (%)	10.8	10.8	18.2	17.3	17.8	28.0	13.9	12.0	31.5	15.4	8.3	28.3
	Weekly worked hours	44.4	44.3	45.3	43.9	43.3	44.0	44.5	44.8	42.1	42.0	40.3	42.2
	Hourly Wage	$3023	$2229	$3598	$1694	$1599	$2894	$3418	$2696	$3222	$2719	$2565	$2617
	Observations	*1953*	*1834*	*18659*	*207*	*167*	*13162*	*3106*	*2375*	*90666*	*668*	*331*	*46655*
2017	Age	35.3	35.1	41.7	35.8	35.4	43.3	36.0	34.8	43.7	36.5	38.4	44.2
	Female (%)	60.2	61.3	52.0	52.4	59.6	53.4	52.2	52.3	53.8	52.3	55.4	52.3
	Schooling	10.9	10.8	11.5	12.0	11.7	10.7	12.8	12.5	11.1	12.5	13.6	10.0
	Income Poverty (%)	14.6	15.1	4.6	15.7	17.0	9.9	6.7	6.6	9.3	13.5	12.9	15.8
	Multi-Dimensional Poverty (%)	31.9	33.9	14.6	29.4	24.2	22.0	19.9	23.7	17.4	10.5	8.3	21.5
	Less than 5 years in Chile (%)	35.7	38.5	-		54.0	61.0 -		57.0	61.0 -	39.3	67.4	-
	Employed (%)	71.0	70.8	53.1	63.0	65.2	50.2	73.5	76.7	54.3	63.8	74.3	50.6
	Unemployed (%)	4.3	4.4	4.2	6.3	3.2	5.0	4.4	3.9	4.4	3.6	0.9	3.4
	Informal (%)	15.5	15.6	26.0	33.0	34.9	37.5	31.6	13.5	15.5	21.2	20.4	29.0
	Weekly worked hours	46.0	45.4	45.9	43.7	43.6	44.5	44.6	44.9	42.5	42.0	40.3	42.2
	Hourly Wage	$2426	$2122	$3094	$2427	$2095	$2387	$3701	$3202	$2794	$3513	$5288	$2237
	Observations	*994*	*947*	*12532*	*311*	*167*	*20053*	*2558*	*1709*	*128097*	*373*	*100*	*47812*

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.

In addition, in the Great North there are signs of negative hierarchical sorting (at least on the basis of observables), since immigrants who settle in that area tend to have lower educational levels and lower salaries compared to natives, which is especially true for Group 2. All of this highlights the importance of considering the heterogeneities present among immigrant workers given that different types of workers locate on different regions.

In summary, both groups have very different labour and socio-demographic characteristics to make a simple comparison nnd analysis of wage differentials. It has been verified that both groups have different levels of education, different average ages, that immigrants apparently arrive in Chile with the aim of working, and that they are concentrated in different geographical areas and economic sectors. Also their skill distributions vary immensely within areas. Therefore, the comparison methodology should take into account the differences between the groups to have a more accurate estimation of the real gaps.

5 Empirical Strategy

Studies attempting to quantify the magnitude of unexplained wage gaps have traditionally used the Oaxaca-Blinder (O-B) decomposition (Oaxaca, 1973; Blinder, 1973) on models similar to (2). This makes it possible to separate the gap between the groups studied into a component explained by observable characteristics and an unobserved one, which would correspond to discrimination. However, this technique, when comparing individuals with totally different characteristics, tends to overestimate (underestimate) the importance of the unexplained component and thus the magnitude of the discrimination if it exist (Ñopo, 2008).

It was found that immigrants who come to Chile in search of job opportunities are very different in their characteristics from the native population, so we are facing, at least in observables, the classic selection problem. In the sample analysed there are combinations of characteristics (age, schooling, occupation levels, etc.) that are typical for migrants, but not for natives and vice versa, so there are notable differences in the supports of immigration.

With this in mind, an attempt will be made to break down the wage gap between natives and immigrants, taking into account the differences in the distribution of their characteristics. The proposed approach is a non-parametric one developed by Ñopo (2008), based on taking the country of birth as treatment and using a matching procedure to select sub-samples of natives and immigrants, to assure that there are no differences in the observable characteristics of the paired observations. With this procedure, the total wage gap between both groups can be broken down into four terms:

$$\Delta = (\Delta_X + \Delta_I + \Delta_N) + \Delta_0 \tag{5}$$

Being Δ_X the component of the gap caused by differences in observable characteristics between groups; Δ_I the part of the absolute gap that arises from the existence of immigrants who have combinations of characteristics that not exists among natives; Δ_N the part of the gap that arises from natives with combinations of characteristics impossible to find among immigrants. Finally, of particular interest is Δ_0, the component that cannot be explained by the characteristics of individuals, possibly attributed to discrimination among other things.

In equation (5) it can be seen that three components can be attributed to observable characteristics of individuals (X, I, N), and the fourth (0) to the existence of a combination of unobservable characteristics and discrimination. Then, it can be interpreted as traditionally has been done within the framework of the O-B decomposition over linear equations, with two components; one that can be explained by differences in observable characteristics and one that cannot be explained by them.

In order to establish a common support to calculate the exact value of the components of the gap, Ñopo's matching algorithm (2008) is used, which is based on 5 steps:

i) Choose an immigrant without replacement of the sample;

ii) Select all natives equal in characteristics to the said migrant;

iii) Create a synthetic individual with the average wage of those chosen in the second step;

iv) Match that individual to the immigrant chosen in step (i);

v) Repeat steps 1 to 4 until the sample of immigrants is exhausted.

With this algorithm we obtain three sub-samples: (a) native persons whose characteristics are not similar to the characteristics of any immigrant; (b) immigrants whose characteristics are not similar to those of any native, and; (c) immigrants and paired natives, with identical characteristics. This group of comparable individuals establishes the common support. On the other hand, the two unpaired groups allow us to calculate the part of the gap that is due to the differences in characteristics existing between natives and immigrants.

This methodology presents some additional advantages over approaches based on the estimation of salary equations, since it does not require strong parametric assumptions so we don't have extrapolation problems that are persistent when estimating via ordinary least squares (Imbens, 2015). Also, it is immune to selection problems on the basis of observables. However, it is not exempt from limitations, since the greater the number of variables included, the smaller the number of paired observations. Therefore, a more reliable estimate of the wage gap is obtained, but for a smaller fraction of the sample.

6 Results

To carry out the matching procedure, the hourly wage of the individual's main occupation is used as the dependent variable and 4 combinations of observable characteristics (specifications) are used. First, a set of demographic variables are used, which we will call specification (1):

1. Sex, age, region of residence, schooling and potential experience of the individual[14] .

Then work characteristics of people are included, but in a different way. Not having an a priori belief in which of these variables is "less endogenous" than the rest, and due to the strong correlation between some of them, as in Ñopo (2004), we opt for their inclusion separately to the complete set of demographic characteristics. This avoids drawing conclusions that probably depend on the order in which each variable is included. Finally, the complete set of observables is included. Thus, we obtain the following specifications:

2. Add to (1) the occupation of the individual to 1-digit level according to the ISCO classification.
3. Adds to (1) the economic sector of the main occupation of the individual to 1-digit level according to the ISIC classification.

[14] This variable is considered within the first group since its construction is done with the age and schooling of the individual.

4. Complete set: Sex, region, age, schooling, potential experience, occupation and sector.

In addition, results are presented separately using as the "treated" group the full sample of immigrants (Group 1), then those from countries with a high Afro-descendant or Hispanic population (Group 2), and finally (for the general results) those from countries different than Group 2 (Group 3), in order to approximate to the existence (or not) of ethnic considerations in the determination of their salary.

6.1 Decomposition of the Migratory Wage Gap

First of all, with the addition of more variables, a shrinkage in the common support can be noted in table 4, since the probability of finding an exact match decreases with the number of characteristics considered. This allows to conclude that, immigrants and natives, are eminently different in their observable characteristics, as there are subsets of covariables which are not easily found within the native population and vice versa. Proportionally, this change is more marked in the native population, since, as Borjas shows (1994, 1999), self-selection in the immigration decision results in similar persons migrating to the host country, so the variation in their characteristics will be less pronounced than that among native population[15].

When comparing Group 1 with the Native population, it can be seen in table 4 that the total gap in both 2015 and 2017 is favourable to immigrants, although in the latter in a notorious smaller magnitude, receiving on average 28% and 6% more than the average wage of natives respectively. This fact reflects a marked deterioration of the immigrant population as a whole, but this result must be interpreted with caution because it can vary greatly if their countries of origin are considered.

Focusing on the first specification, columns (1) and (2) of table 4 and show that, when considering only demographic variables in the algorithm, the larger part of the absolute gap remains unexplained, with large (in absolute value) and statistically significant values for Δ_0 which is equal to 21% and -12% of the average wage of natives in 2015 and 2017 respectively. Note that the analysis of this component alone then also reflects the mentioned deterioration of their relative situation compared to that of the native population. Also, Δ_X is equal to 1% in 2015 and 14% in 2017, being statistically significant only in the second period. This is to say, that if the distribution of demographic characteristics between

[15]This reinforces the idea that immigrants are not a random draw from their countries of origin.

Table 4: Decomposition of the Migratory Wage Gap Group 1, 2015 and 2017.

	(1)		(2)		(3)		(4)	
	2015	**2017**	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**
Δ	0.28	0.06	0.28	0.06	0.28	0.06	0.28	0.06
Δ_0	0.21***	-0.12***	0.39***	0.04***	0.38***	-0.04***	0.26***	0.04***
	(0.009)	(0.008)	(0.014)	(0.011)	(0.015)	(0.012)	(0.017)	(0.018)
Δ_I	0.00	0.00	0.01	-0.01	0.01	0.00	0.00	0.02
Δ_N	0.06	0.05	0.13	0.10	0.08	0.08	0.08	0.09
Δ_X	0.01	0.14***	-0.23***	-0.07*	-0.18**	0.02	-0.06	-0.08**
	(0.072)	(0.035)	(0.074)	(0.037)	(0.076)	(0.037)	(0.083)	(0.040)
% Immigrants	99.2	99.3	96.8	96.9	95.0	95.1	87.6	85.8
% Natives	73.0	74.9	50.4	52.0	41.4	43.2	26.4	27.2

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.
Standard errors in parentheses. * $p \leq 0.1$; ** $p \leq 0.05$; ***, $p \leq 0.01$.

groups were equal, immigrants would earn 28% more than natives in 2015 and -12% less in 2017.

We now turn to specifications (2) and (3). This is done because a common path followed in the wage gap literature has been to determine whether there are individuals belonging to a particular group who manage to be employed in highly paid jobs, which the other group is unable to reach. In this case, it can be said that part of the wage gap is attributable to the existence of occupational segregation in the labour market. At the same time, sectoral segregation may also exist if the members of the group suspected of discrimination do not succeed in being employed in highly remunerated sectors, regardless of their endowments.

For the second specification, columns (3) and (4) of table 4 reflects substantial changes in all the components with respect to what has been shown so far. For example, the magnitude of Δ_0 increases substantially in both periods, being near 39% in 2015 and 4.0% in 2017, both statistically significant at all levels. This change occurs along with two others that deserve attention; First Δ_N (natives with no immigrant peer) grows substantially, which is to say that the occupational distribution between immigrants and natives is very different. For its part, Δ_X decreases by a considerable magnitude, changing sign with respect to (1) in both periods, and being statistically significant at a 99% in 2015, and at a

90% in 2017[16].

Now turning our attention to the third specification, it can be seen in columns (5) and (6) of table 4 that Δ_0 is near 38% in 2015 and near -4.0% in 2017 for Group 1, both statistically significant with 99% of confidence. At the same time, as in the previous specification, Δ_X experienced a reduction, but taking negative value and being statistically significant (at a 95% confidence) only in 2015. Also this reductions are more modest than the ones originating from the inclusion of occupation, since Δ_X takes values of -18% and 2% in 2015 and 2017, while in the previous case those values were of -23% and -7% respectively.

Finally, the last specification considers all the variables used before. It can be seen that in column (7) of table 4 that in 2015 Δ_0 is equal to 26.0%, near 100% of the total gap and statistically significant at all levels. In the year 2017 this becomes 4.0% (statistically significant at all levels) but in relative terms it is of near 75% of the absolute gap. For its part Δ_X is equal to -6% in 2015 and -8% in 2017, only the latter being statistically significant at a 95% of confidence. Also, the components related to individuals outside the common support take positive values, which means that natives inside the common support are better endowed than those outside, and that immigrants inside it are worst endowed than those outside it[17].

The analysis of Group 2 reveals similar patterns than that of Group but also stronger. Table 5 shows a clear deterioration of their relative situation within only 2 years, since in 2015 the absolute gap was 11.7% and by 2017 the absolute gap changes sign and takes a value of -16.3%. Proportionally this means that in the course of only 2 years the absolute gap was reduced in a striking 239% for group 2. Columns (1) and (2) of table 5 show smaller Δ_0 than that of Group 1 in both years, with values of 15% and -26% respectively and also smaller values for Δ_X, being statistically significant only in 2017.

When comparing Natives and Group 2 after the inclusion of the occupation variable, similar phe-

[16] In general, Δ_X have larger standard errors than Δ_0. This is because standard errors for Δ_0 are constructed using the distribution of hourly wages of natives and those for Δ_X use the wage distribution of immigrants, which has a larger variance, more details in the Appendix.

[17] This means that either immigrants inside the common support ar worst endowed in terms of their demographic characteristics and/or that they are employed in occupations or sectors with lower earnings potential.

Table 5: Decomposition of the Migratory Wage Gap Group 2, 2015 and 2017.

	(1)		(2)		(3)		(4)	
Year	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**
Δ	0.12	-0.16	0.12	-0.16	0.12	-0.16	0.12	-0.16
Δ_0	0.15***	-0.26***	0.42***	-0.07***	0.26***	-0.19***	0.21***	-0.09***
	(0.011)	(0.008)	(0.016)	(0.010)	(0.018)	(0.012)	(0.021)	(0.014)
Δ_I	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.02	-0.02
Δ_N	0.07	0.04	0.11	0.07	0.03	0.01	0.01	0.00
Δ_X	-0.10	0.06***	-0.41***	-0.15***	-0.17*	0.02	-0.08	-0.05**
	(0.089)	(0.021)	(0.092)	(0.022)	(0.096)	(0.022)	(0.105)	(0.024)
% Immigrants	99.1	99.3	96.6	97.0	94.6	95.4	88.3	87.0
% Natives	64.5	70.8	42.2	46.6	33.2	38.0	21.2	23.7

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.
Standard errors in parentheses. * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

nomena is observed in columns (3) and (4) of table 5, although, the changes in the relevant components compared to those of Group 1 are greater in both years. It is also observed that in 2017, as with Group 1, there is a reduction in absolute value of Δ_0 which means that the absolute gap would be closer to 0 assuming equality of distributions of observables between groups. This with the negative and statistically significant magnitude of Δ_X means that differences in occupational distributions (and perhaps segregation in the sense of not being able to ascend to highly paid occupations) can explain a great deal of the absolute gap for both groups. We will go back on this issue later.

With the inclusion of sector, columns (5) and (6) of 5 show an increase of Δ_0 respect to specification (1) taking values of near 26.0% in 2015 and near -19.0% in 2017, accompanied by a decrease in Δ_X in both years, although in a smaller magnitude than that of specification (2). All of this suggests that, if both Groups 2 where subjected to sectoral segregation, it would be of lesser intensity than occupational segregation, fact supported by Δ_X being only significant at only a 90% confidence in 2015.

It can be seen in column (7) of table 5 that in 2015, the unobservable component takes a value of 21.0%, statistically significant at all levels while it deteriorates greatly in 2017, taking a value of -9.0% in 2017 also significant at all levels as it can be seen in the eight column of table 5. Also, Δ_X take negative values in both years, being of -6% in 2015 and -8% -significant at a 95%- in 2017. Also, Δ_I is equal to 2% both in 2015 and 2017, which means that in both years immigrants from Group 2 outside the common support are better endowed than those inside.

Table 6: Decomposition of the Migratory Wage Gap Group 3, 2015 and 2017.

	(1)		**(2)**		**(3)**		**(4)**	
Year	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**
Δ	0.88	1.57	0.88	1.57	0.88	1.57	0.88	1.57
Δ_0	0.26***	0.51***	0.20***	0.46***	0.35***	0.68***	0.21***	0.57***
	(0.010)	(0.019)	(0.013)	(0.025)	(0.014)	(0.022)	(0.020)	(0.035)
Δ_I	0.01	-0.01	0.05	-0.03	0.07	0.02	0.06	0.14
Δ_N	0.10	0.11	0.23	0.32	0.17	0.26	0.24	0.38
Δ_X	0.51***	0.95***	0.41***	0.82***	0.29***	0.60***	0.38***	0.47**
	(0.097)	(0.189)	(0.092)	(0.196)	(0.090)	(0.200)	(0.099)	(0.230)
% Immigrants	99.7	99.3	97.4	96.2	96.4	93.1	85.0	77.9
% Natives	58.8	58.1	33.8	30.1	26.6	21.5	13.9	11.5

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.
Standard errors in parentheses. * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

The large differences found between groups motivate the realization of the same exercise for those immigrants who are not included in Group 2, since although considerably smaller than Group 2, it must be pushing the results obtained upwards, reflecting great wage inequalities between immigrants. Now onwards this group will be called Group 3. Focusing our attention to table 6, first it can be seen that, contrary to Group 2, their relative situation respect to natives improved between 2015 and 2017. This manifests through their total relative gaps which were near 88% in 2015 and 157% in 2017.

For its part, using specification 1, Δ_0 takes positive and large values, with a 26% of the average hourly wage of natives in 2015, increasing to a 51% in 2017 statistically significant at all levels. Also, unlike the previous cases, most of the total gap can be explained by their demographic endowments, since Δ_X explain more than 50% of the total gap. Taking into account specifications 2 and 3 for Group 3, the pattern is similar (table 6) than what we saw before, this is to say, increases in Δ_0 accompanied with reductions in Δ_X, but without the sign reversal observed before. But the large and positive values taken by Δ_0 and Δ_X in both specifications let us disregard completely sectoral segregation for this group.

For specification 4 we conduct an in/out of support analysis in order to get a broader picture about the sign and magnitude of the estimated components of the absolute gap. It can be seen in table 14 of the Appendix that in both years, immigrants from Group 1 within the common support are on average younger and exhibit a smaller proportion of females, facts explained by the nature of the matching algorithm, since it matches one immigrant to many natives. Also, we can see in tables 14 and 15 that both groups exhibit similar levels of income poverty in 2015, and differences exacerbate in 2017, responding to the deterioration in the relative situation of immigrants. For multidimensional poverty it can be seen in the table that immigrants are on average poorer, with differences over 4 percentage points in both years. Moreover, for Group 2 within the support in both years it can be seen that sex differences are almost negligible and both measures of poverty are more accentuated.

Turning our attention to schooling and potential experience it can be seen in the same table that, on average, schooling levels between both groups inside the common support are more ore less similar in both years with a greater difference in 2017 in favour to the immigrants, and specially high for Group 2, while natives tend to be more experienced in both periods. This means that while considering that schooling is the only variable with a strictly positive relation with wages, the deterioration of their relative situation may not respond to recent migratory inflows composed of worst endowed workers and has to do with other aspects that will be analysed further. For example Group 2 would be subjected to a larger differential if distributions of skills compared to those of natives were the same, which somewhat compensate the effect of the addition of occupation and sector dummies over Δ_X and Δ_0.

In summary, it has been shown that over the course of just two years, the relative situation of immigrants relative to natives has deteriorated markedly, especially for those from countries with a high Afro-descendant or Hispanic ascendancy, who have seen the absolute wage gap taken negative values, added to negative (and statistically significant) values for Δ_0, the component that cannot be explained by observable characteristics of the individual.

Also, the suspicion of occupational and sectoral segregation motivates a more detailed review of the phenomenon, considering that the true cause of the observed results could attend to the scarce time of permanence in Chile of an important part of them, since we cannot relate the values of the components directly to segregation without taking into account the year since arrival of immigrants. This is because as the assimilation literature points out, immigrants may take some time before acquiring country specific abilities positively valued in the host country labour market, and gaps could be reflecting this and not discrimination alone. The next subsection will be devoted to this analysis, only taking into account Group 2, the one suspect of segregation.

6.2 Decomposition of the Wage Gap considering time of arrival

The subsequent analysis in conducted on the basis that immigrants with different lengths of stay in the country may differ in their observable and unobservable characteristics. As Borjas establishes (1999), they may differ in their skills at their time of arrival and its relative sustituibility or complementarity with those acquired in the host country. At the same time, while acquiring those skills, immigrants may face a process of wage assimilation too, making their wages more similar to those of the native population as times passes, so potential segregation within occupations or sectors has to do more with this process itself than a migratory "glass ceiling effect".

This phenomenon may originate because it takes time to acquire a set of skills specific to the host country, valued positively in the labour market, or immigrants are employed in jobs below their true ability, since for various reasons they may face occupational barriers and only after a few years, may climb to occupations commensurate with their endowments. In this sense, occupational/sectoral segregation can be confounded with this type of dynamic since it may be that in order to climb to highly paid positions, immigrants must spend time in the local labour market in order to acquire the necessary specific skills to do so. This means that higher Δ_0 accompanied by lower Δ_X cannot be identified as segregation upon the addition of occupational/sectoral variables if the time of stay is not taken into account.

Tables 7 and 8 separates immigrants from Group 2 into two cohorts, appealing to the literature on wage assimilation. Based on the evidence presented in Chiswick (1978), it has documented that, at the time of their arrival in the host country, immigrants generally earn lower wages in relative terms, experiencing gradual increases over time (Lalonde and Topel, 1997; Borjas, 1995; Algan et al, 2010). Attending to this, second group immigrants have been classified depending on whether they have been in Chile for more or less than 5 years[18] .

Table 7: Decomposition of the Migratory Wage Gap, Cohort 1, 2015 and 2017.

	(1)		**(2)**		**(3)**		**(4)**	
	2015	**2017**	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**
Δ	-0.01	-0.26	-0.01	-0.26	-0.01	-0.26	-0.01	-0.26
Δ_0	-0.16***	-0.35***	0.00	-0.18***	0.24***	-0.25***	0.06***	-0.13***
	(0.014)	(0.009)	(0.013)	(0.012)	(0.016)	(0.015)	(0.020)	(0.021)
Δ_I	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02
Δ_N	0.06	0.03	0.06	0.02	0.02	-0.01	-0.02	-0.03
Δ_X	0.09*	0.07***	-0.06	-0.09***	-0.26***	0.01	-0.03	-0.07***
	(0.059)	(0.019)	(0.061)	(0.020)	(0.063)	(0.020)	(0.068)	(0.023)
% Immigrants	99.4	99.4	96.5	97.4	95.3	96.2	88.4	87.0
% Natives	47.3	59.1	29.8	35.0	22.0	29.9	11.8	17.6

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.
Standard errors in parentheses. * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

Inspection of table 7 shows that the absolute gap of those with 5 or less years of residence from Group 2 decreased from being -1.0% in 2015 to -26.0% in 2017. Meanwhile for the second cohort (table 8) the absolute gap between both years decreased from 21.0% to -2.0%. This makes it possible to venture that the assimilation process for some reason has lost strength among Group 2 immigrants during the last few years, since those with a considerable time in Chile end up receiving salaries that are on average lower than those of the natives.

We now turn to specification 2 to get closer to the verification of the existence of occupational segregation. For the first cohort it can be seen in column (3) of table 7 that in year 2015 the inclusion of occupation raises the unexplained component of the gap by sixteen percentage points, not being sig-

[18]To simplify the exposition, sometimes from now on those from the 5 or less years cohort will be called ''Cohort 1'' and the other one ''Cohort 2''.

Table 8: Decomposition of the Migratory Wage Gap, Cohort 2, 2015 and 2017.

	(1)		**(2)**		**(3)**		**(4)**	
	2015	**2017**	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**
Δ	0.21	-0.02	0.21	-0.02	0.21	-0.02	0.21	-0.02
Δ_0	0.24***	-0.06***	0.50***	0.10***	0.25***	-0.04***	0.21***	0.01
	(0.013)	(0.010)	(0.016)	(0.012)	(0.017)	(0.013)	(0.021)	(0.018)
Δ_I	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.02	-0.02
Δ_N	0.09	0.08	0.12	0.11	0.03	0.02	0.01	0.01
Δ_X	-0.12	-0.04	-0.40***	-0.23***	-0.06	0.01	0.01	-0.01
	(0.145)	(0.040)	(0.150)	(0.042)	(0.155)	(0.043)	(0.168)	(0.046)
% Immigrants	98.9	99.2	96.6	96.4	94.0	94.3	88.2	86.9
% Natives	57.7	61.4	37.2	36.7	28.7	29.1	17.7	16.8

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.
Standard errors in parentheses. * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

nificant at any level. Also Δ_X decreases from 9% to -6%, the latter not significant at any level. In 2017 it can be seen a similar and stronger pattern in column (4) with greater changes in both components. These changes are expected, first because of the deterioration in the relative situation of immigrants and second because this cohort is supposed to be the one with greater difficulties in ascending to highly paid occupations.

Inspection of columns (3) and (4) of table 8 reveals a huge change in Δ_0 for the second cohort, passing from 24% to 50% in 2015 and from -6% to 10% in 2017. This accompanied by an equally huge change in Δ_X, which passes from -12.0% to -40.0% in 2015 and from -4.0% to -23.0% in 2017, all significant at a 99% confidence. This means that immigrants of Group 2 within the "more than 5 years" cohort inside the common support, either have worse endowments than their native counterpart, or they are subjected to occupational segregation, forcing them to work in lower remunerated sectors. This is striking considering that they have already been in the country for a prudent time to have gone through the process of assimilation and maybe they experience what is called in the literature a glass ceiling effect. Also, if this assertion were true, differences in the relevant components should be lower once we control for sector (i.e immigrants with high earning potential occupations work in lower remunerated sectors).

Table 17 of the appendix reveals that the reported changes in Δ_0 and Δ_X with the inclusion of occupational dummies, all else being equal, may attend to worst endowments in terms of schooling once we control by occupation, since within this cohort immigrants exhibit on average 0.8 and 0.4 years less than natives in 2015 and 2017 respectively. But changes in these values are modest if we compare with the average schooling of immigrants and natives within the common support for specification one (table 16), which is almost the same. Considering this, the movement in both components have to come almost certainly from some type of occupational segregation towards group 2 immigrants, regardless of their time in Chile.

Now we turn our attention to the inclusion of sector. It can be seen in columns (5) of table 7 and that its inclusion bring similar changes to the relevant components than the previous case, but modest in magnitude. In particular, for the first cohort Δ_0 jumps from -16% to 24% in 2015 and from -35% to -25% in 2017, all statistically significant at all levels. Meanwhile Δ_X changes by minus thirty five percentage points in 2015 and minus six percentage points in 2017, losing it significance for the second period.

For the second cohort suspicions of sectoral segregation are not as strong as that of occupational segregation, since it can be seen in columns (5) and (6) of table 8 that in 2015 Δ_0 jumped from 24.0% to 25.0% with the inclusion of sectoral dummies, meanwhile in 2017 jumped from -6.0% to -4.0%, all statistically significant at 99% of confidence. At the same time in both years we observe larger Δ_X but changes in absolute values are smaller than those experienced with the inclusion of occupational dummies and it doesn't have any significance.

In terms of schooling (table 18), as it was the case with specification 2, immigrants from the second cohort within the common support are worst endowed than their native counterpart during both years, although differences between groups are in general smaller than those found using specification 2 and also from those found using specification 1. This along with the larger movement of Δ_X compared to that of Δ_0 allow us to discard any form of strong sectoral segregation.

Finally, for the sake of completeness, the full set of variables is used. It can be seen in columns (7) and (8) of tables 7 and 8 that in 2015 both cohorts exhibited a positive Δ_0, statistically significant at all levels. This somewhat differs from what happens in the year 2017, since their values are reduced, even becoming negative for the first cohort (-13.0%, significant at all levels). On the other hand, Δ_X is positive only for cohort 2 in 2015, with values of -3.0% and 1.0% respectively. These values change in 2017, since the component is reduced for both cohorts only significant at a 99% for the first one. All these results are in line with the assertion that regardless of their occupation, immigrants concentrate in sectors with lower remunerations.

6.3 Beyond the Central Zone: Geographical Decomposition of the Gap

Table 9: Decomposition of the Migratory Wage Gap, Group 1 by geographical zone, 2015-2017.

	Great North		**Little North**		**Central Zone**		**South Zone**	
Year	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**
Δ	-0.22	-0.16	0.02	-0.41	0.32	0.06	0.57	0.04
Δ_0	0.04	-0.15***	-0.09***	-0.05*	0.27***	0.07***	0.33***	0.08***
	(0.036)	(0.037)	(0.025)	(0.026)	(0.012)	(0.013)	(0.021)	(0.016)
Δ_I	-0.03	-0.02	0.03	0.01	0.04	0.01	0.02	0.04
Δ_N	-0.17	-0.08	-0.04	-0.25	0.00	0.01	0.00	0.02
Δ_X	-0.05	0.08**	0.12	-0.13***	0.01	-0.02	0.22	-0.10*
	(0.058)	(0.044)	(0.087)	(0.023)	(0.100)	(0.051)	(0.195)	(0.053)
% Immigrants	76.0	82.6	79.4	74.5	95.9	94.4	86.0	86.6
% Natives	32.7	42.6	19.8	15.9	48.7	50.1	22.0	26.6

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.
Standard errors in parentheses. * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

In table 2 it can be seen that the spatial concentration patterns of immigrants are very different from those of natives as they tend to agglomerate in the Great North and Central Zone of the country. Also, it was seen that more than 70% of immigrants and about 50% of natives are concentrated in the Central Zone of the country, taking away a large part of the weight of the averages. In addition, labour markets are very different geographically, so their particularities could have an effect on the emergence of unexplained gaps.

Table 10: Decomposition of the Migratory Wage Gap Group 2 by geographical zone, 2015-2017.

	Great North		**Little North**		**Central Zone**		**South Zone**	
Year	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**	**2015**	**2017**
Δ	-0.31	-0.38	-0.12	-0.45	0.15	-0.16	1.36	-0.02
Δ_0	0.02	-0.17***	-0.16***	-0.06**	0.20***	-0.03***	0.69***	0.02
	(0.036)	(0.038)	(0.026)	(0.026)	(0.013)	(0.011)	(0.065)	(0.017)
Δ_I	-0.04	0.01	0.00	-0.01	0.02	-0.01	-0.25	-0.01
Δ_N	-0.18	-0.09	-0.10	-0.26	-0.07	-0.08	0.17	0.02
Δ_X	-0.12**	-0.13***	0.14	-0.12***	-0.01	-0.04	0.75	-0.06
	(0.051)	(0.026)	(0.096)	(0.023)	(0.127)	(0.031)	(0.580)	(0.068)
% Immigrants	75.7	81.7	80.6	76.7	96.9	94.8	79.1	88.0
% Natives	32.1	40.4	18.1	13.8	41.1	43.8	8.3	18.6

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.
Standard errors in parentheses. * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

All of the above justifies a geographical analysis, given that in certain geographical areas the relative situation of immigrants may be different from the national average. In fact, revision of table 3 shows that, for example, in the Great North, unlike the national average and what happens in the rest of the country, immigrants have, for example, lower levels of schooling than natives. Considering this, one can be in the presence of a "negative hierarchichal sorting" in the sense of Borjas (1987, 1999), where the most compressed salary structure, compared to that the Central Zone[19], could cause the selection of immigrants in that zone to be made from the bottom of the income distribution of their countries of origin.

For this exercise, only the complete set of observable variables will be used. In fact, as it was seen from the characterization carried out for the immigrants of the Great North, it is observed in tables 9 and 10 that in both years the absolute gap is negative for both groups of immigrants. However, contrary to the generalized trend its lower in absolute value in 2017 (-16.0%) than 2015 (-22.0%) for Group 1. On the contrary, and in line with the generalized trend for Group 2 the absolute gap goes from -31.0% of the average salary of natives in 2015 to -38.0% in 2017.

[19]In fact, in 2017 the GINI coefficient from wages is not higher than 0.41 in Great North regions, while in the Metropolitan region is equal to 0.49, more detail in table 13 of the Appendix.

For group 1, the value of Δ_0 is 4.0% in 2015 and -15.0% in 2017, only this one being statistically significant. For Group 2 its values are 2% in 2015 and -17% significant at all levels in 2017. For its part, Δ_X is negative only in 2015 for Group 1 without any significance. Also it is negative in both years for Group 2, taking values of -12% and -13% respectively, both significant at least at a 95% confidence.

In the Little North and for both groups, the absolute gap has gone through an enormous change between both years, going from 2% to -41% in group 1 and from -12% to -45% between both years. The component attributable to unobservables is negative a for both groups in both periods, all statistically significant to different degrees. A different fact to what happens in the Great North is the marked deterioration and change of sign of Δ_X for both groups in the course of the two periods studied. According to the information provided in the table 3 there has been no reduction in the educational level of immigrants living in this area, so necessarily between both years occupational or sectoral segregation have emerged or at least intensified their level.

On the other hand, in the Central Zone, the value of the absolute gap is positive for Group 1 during both years, although a clear deterioration is observed since this goes from 32% of the average salary of the natives in 2015 to 6% in 2017. Similarly, the aforementioned deterioration also occurs for group 2, although in this case for 2017 the absolute gap becomes negative, indicating that in an area that by its characteristics should attract immigrants selected positively from the distribution of their countries of origin (i.e with high earnings potential), the hypothesis that these reach the top of the wage distribution is not fulfilled completely.

In fact the part of the gap that cannot be explained by the characteristics of individuals also had a notable deterioration, going for Group 1 from 27% in 2015 to 7% in 2017 and from 20% to -3% for Group 2, all statistically significant at 99%. This is accompanied by a modest change in Δ_X, which becomes negative between the two periods considered for group 1 and more negative for Group 2, but without any significance. This shows that in the Central Zone the deterioration is not at all due to a worsening in the endowments of immigrants and it can be explained either because of an intensification of segregation or aspects beyond what can be explained by demographic or labour characteristics.

Finally, in the Southern Zone an even more notable deterioration of the relative situation of immigrants is observed with respect to the other 3 zones considered in this analysis. For example, the absolute gap decreases by nearly 53 percentage points for Group 1 and by more than 138 percentage points for Group 2 (becoming negative). In fact in 2015, and contrary to what has been the tonic of the last exposed results, the absolute gap and the unobservable component are specially large for Group 2, which shows that in this period immigrants from this group only migrated towards the south (most remote area of the country) in presence of really attractive job opportunities.

The decrease in the absolute gap mentioned above, is accompanied in 2017 by a drastic change Δ_0, going from 33.0% to 8.0% for Group 1, and from 69.0% to 2.0% for Group 2, although this last one is not significant at any level. This result is intriguing, since as shown above, there has been no evident deterioration in the level of human capital of those immigrants who arrive in this area and in general the newly arrived cohorts boast higher levels of schooling. This is accompanied by considerable changes in Δ_X which in both cases undergoes a change of sign. All of this points out also to a intensification of segregation in this zone.

7 Robustness Checks

One question that remains unanswered is to what extent the results obtained using the matching approach differs from those obtained using linear regressions and performing the Oaxaca-Blinder decomposition over the results obtained. This exercise also allow us to test the validity of the methodology, in the sense that results from both shouldn't differ to a great extent if the linear estimation is performed with the same set of matching variables over the common support (Ñopo, 2008).

To this end, linear regressions were performed utilizing a saturated model, (i.e regression models with discrete explanatory variables, where the model includes a separate parameter for all possible values taken on by the explanatory variables included). This was done considering that the matching algorithm used previously groups individuals into categories defined by distinct variables values and because this procedure allows us to get closer to a set-up that has lower dependence on the functional form of the earnings equations, as is the case for matching. This is due to the fact that in estimating a saturated model by ordinary least squares the conditional expectation function to approximate is indeed linear in the dummies utilized (Ñopo, 2008; Angrist & Pischke, 2008.).

Another point to be made is that the matching procedure uses $\frac{\overline{w_I}}{\overline{w_N}} - 1$ to obtain the absolute gap between groups while generally the gap in linear regression approach is $\overline{ln(w_I)} - \overline{ln(w_N)}$. This is due to reasons exposed with detail in Ñopo (2004, 2008). Considering this, our calculation of the components of the gap using linear regressions uses the former measure of the absolute gap to obtain results with greater comparability. Oaxaca-Blinder methodology then is performed for specifications 1 and 4 using the pooled sample (no common support is established) and the sample within the common support, obtained using the same criteria of Ñopo decomposition (matching in observables).

Table 11: Decomposition of the wage gap using O-B and Ñopo Match for Group 1, 2015 and 2017†.

Year		**Specification 1**			**Specification 4**		
		O-B (NCS)	**O-B (ICS)**	**Ñopo**	**O-B (NCS)**	**O-B (ICS)**	**Ñopo**
2015	Δ_0	0.16***	0.16***	0.21***	0.18***	0.21***	0.26***
	Δ_X	0.11***	0.05***	0.01	0.10***	-0.02***	-0.06
2017	Δ_0	-0.12***	-0.11***	-0.12***	-0.04***	-0.04***	0.04***
	Δ_X	0.18***	0.13***	0.14***	0.10***	-0.005**	-0.08**

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.
Standard errors in parentheses. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
† NCS stands for no common support and ICS for inside the common support.

In table 11 show that Ñopo decomposition results in larger values for the unexplained component in all cases. Also, values for this component show more similarity between the O-B decompositions than any of them compared to that obtained by Ñopo decomposition. Anyway, for all periods results are more or less similar between methodologies, with the highest difference of eight percentage points in 2017 for specification 4 (-4,0% with both O-B and 4.0% with Ñopo decomposition).

The slight differences found have to do with the weighting schemes used by both methodologies to obtain Δ_0. In fact, it can be demonstrated that in the O-B framework the unexplained component is the average treatment effect on the treated (ATT) (Słoczyński, 2015). So, because of the use of linear regressions with a saturated model, the ATT can be expressed as a variance weighted average of each covariate specific treatment effect (Angrist & Pischke, 2008). On the other hand Ñopo decomposition weights those covariate specific effects using the empirical distribution of covariates among the untreated (natives), so naturally both weighting schemes will result in different estimators of the unexplained part of the wage gap.

The observed component tend to be more similar between Ñopo and O-B inside the support than between both O-B decompositions, with the higher difference of almost eight percentage points also observed in 2017 for specification 4. The argument for the differences is more or less similar than the one exposed on the previous paragraph. An important difference between both methodologies is that O-B uses the control group outcome to obtain Δ_X while Ñopo decomposition use the treatment group outcome, both with specific weights. So, even in the case of equality of weights, different results can be expected if outcomes are different between groups.

Finally it can be observed in table 11 that summation of both components is virtually equal in all years and specifications between O-B performed inside the common support (ISC) and Ñopo decomposition. In this case it can be said that the failure of O-B to recognize differences in the support of individual characteristics between groups, manifest itself through an over estimation of the explained component, which can be expressed as the selection bias in the immigration decision[20] . So, selection bias might become stronger in O-B decompositions if differences in supports are not taken into account.

8 Conclusions and Final Remarks

This document attempts to shed light on the relative situation of immigrants respect to natives in terms of wages, considering the heterogeneities present among the former. At the same time, account is taken of the fact that both groups are eminently different. On average, immigrant workers receive higher wages, have higher levels of education, higher levels of employment and work in different sectors. If the differences in supports are not taken into account, the unexplained component of the gap could be under or overestimated, which necessarily leads to the use of an identification strategy that addresses this problem.

[20]More detail in the Appendix.

In 2015, in accordance with the previous evidence for the case of Chile granted by Contreras et al (2013), and contrary to international evidence, on average immigrants receive higher wages, even considering the ethnic background of the countries of origin as the first source of heterogeneity. In the latter case, however, the differences are smaller. But these conclusions are only valid for this year, since as we have seen, in 2017 took place a generalized deterioration of the relative situation of immigrants, in spite of not being accompanied by deteriorations in the human capital of the most recent inflows.

Moreover, the use of the complete set of variables, in addition to the aforementioned generalized deterioration in the situation of immigrants, shows how especially marked this phenomenon is for Group 2. This is particularly alarming if one takes into account the fact that immigrants subjected to more precarious conditions are under-represented in surveys, so the results presented here can be taken as a reasonable upper bound of the true situation of immigrants in Chile.

When taking into account different sources of heterogeneity, such as the immigrant length of stay in the country or its geographical location, there are some important changes with respect to the general results. Detailed inspection of the situation of both groups of immigrants through the different specifications used shows that effectively the best endowments of immigrants are positively remunerated in the Chilean labour market. From this it can be inferred that the most of the negative gaps that appear around 2017 are related first, to the lack of assimilation of the sizeable recent inflows of immigrants from this group and second to the existence of occupational segregation towards those who have spent more than 5 years in the country.

In particular, the gap for immigrants from countries with a high Afro-descendant or Hispanic component, with less than 5 years of residence is negative, as is the value of the observed and unobserved components. Those are expected results if one takes into account the fact that they are still subject to a process of wage assimilation, in the sense of a constant learning of skills specific to the country's labour market. In addition, when controlling by occupation and/or sector one observes their difficulties in occupying a high rank position, a logical result given their short stay in the country.

Within Group 2, in the cohort with more than 5 years of residence in the country, it is found that, in addition to the negative wage gap they face -a fact that is not in line with international evidence- this comes from the inclusion of occupation and/or sector variables to the complete sociodemographic set. Then, despite having gone through a prudent assimilation time, this group, continues to be subject to occupational segregation. This fact raises suspicions about discrimination against Group 2 in particular or a constituent part of it.

At the same time, the geographical separation shows that in the Northern Zone of the country the gap, and magnitude of the unobserved component, take negative and particularly high values. In fact, in "Norte Grande" there are signs of negative selection in observables, a trend contrary to what occurs in the Central Zone of the country. In this sense, it remains to be determined what mechanisms are behind the different types of selection that seem to be carried out through the different geographical zones of the country, although the more dispersed income distribution of the Central Zone may be a sufficient reason to attract immigrants with higher qualifications, who seek to take advantage of this salary structure. Another important fact is the notable deterioration that occurs in the southern zone in just two years, which shows that gradually it is beginning to configure itself as a valid destination for all types of immigrants, and not only those who respond to really attractive job opportunities.

These results have the potential to motivate new lines of research, such as seeing what happens to the relative situation of immigrants throughout different parts the wage distribution, and verifying whether those subject to the greater gaps are effectively under more precarious conditions than their native counterparts (i.e natives in the same quantile). It is also possible to generate research lines around verifying what happens in different economic sectors and if these results are in accordance with the predictions of the Becker model (1975), considering their level of competitiveness.

Finally, the analysis can be carried out for other subgroups of the immigrant population. In particular, it is interesting to implement this exercise for those who face important language barriers, being of special interest the Haitian population, which has shown great inflows in the last three years. Haitian immigrants make up a group that is highly suspected of discrimination, since in addition to racial considerations in the determination of their salaries, the language barriers they face must also be added.

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9 Appendix

Derivation of the Standard Errors of the Explained Component

The sample analog of the explained component can be expressed as:

$$\delta_X = \bar{y}^I - \sum_X \bar{y}^I(x)\hat{\lambda}^N(x)$$

Where:

- $\bar{y}^I(x)$ the sample average earning of immigrants with the set of characteristics x.

- $\bar{y}^I$ the average earnings of immigrants.

- $\hat{\lambda}^N(x)$ the sample proportion of natives that exhibit the characteristics x.

The variance of the first term of the right-hand side can be easily derived from its asymptotic distribution:

$$\sqrt{n_I}(\bar{y}^I - y^I) \underset{n_I \to \infty}{\to} N(0, \sigma_I^2)$$

At the same time, the second term of the right-hand side is the same than that of Ñopo (2008), so delta method can be used to derive its asymptotic distribution. Let K denote the number of values that x can attain, its variance can be computed as:

$$\sum_{i=1}^{K}\left[\frac{\hat{\lambda}^N(x_i)(1-\hat{\lambda}^N(x_i))}{\alpha^2}(\bar{y}^I(x))^2 + \hat{\sigma}_i(\hat{\lambda}^N(x_i))^2\right]$$
$$-2\sum_{i=1}^{K}\sum_{j=1}^{i-1}\frac{\hat{\lambda}^N(x_i)\hat{\lambda}^N(x_j)}{\alpha^2}\bar{y}^I(x_i)\bar{y}^I(x_j)$$

Which can be used with the empirical counterpart of σ_I^2 to construct the standard errors for δ_X.

Oaxaca Blinder as ATT plus Selection Bias

Let the model for outcomes be linear with flexible coefficients, then we have:

$$Y_i = X_i\beta_1 + u_{1i} \ \text{ if } \ D_i = 1 \qquad \text{and} \qquad Y_i = X_i\beta_0 + u_{0i} \ \text{ if } \ D_i = 0$$

With $E[u_{1i}|X_i] = E[u_{0i}|X_i] = 0$, then:

$$\begin{aligned}
&E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = \\
&= E[X_i|D_i = 1] \cdot \beta_1 - E[X_i|D_i = 0] \cdot \beta_0 \\
&= E[X_i|D_i = 1] \cdot (\beta_1 - \beta_0) + (E[X_i|D_i = 1] - E[X_i|D_i = 0]) \cdot \beta_0 \\
&= E[Y_i(1) - Y_i(0)|D_i = 1] + (E[Y_i(0)|D_i = 1] - E[Y_i(0)|D_i = 0]) \\
&= \tau_{ATT} + (E[Y_i(0)|D_i = 1] - E[Y_i(0)|D_i = 0])
\end{aligned}$$

And from the linear model we know that:

$$\begin{aligned}
E[Y_i(0)|D_i = 0] &= \bar{Y}_0 \cdot \hat{\beta}_0 \\
E[Y_i(0)|D_i = 1] &= \bar{Y}_1 \cdot \hat{\beta}_0
\end{aligned}$$

So we have:

$$E[Y_i(0)|D_i = 1] - E[Y_i(0)|D_i = 0] = (\bar{Y}_1 - \bar{Y}_0) \cdot \hat{\beta}_0 = \Delta_X$$

Suplementary Tables

Table 12: Immigrants by source country, 2018

Country of Birth	Total	Male	Female	Total (%)	Male (%)	Female (%)
1 Peru	187756	87930	99826	25.2	23.8	26.5
2 Colombia	105445	48811	56634	14.1	13.2	15.0
3 Venezuela	83045	42641	40404	11.1	11.6	10.7
4 Bolivia	73796	32146	41650	9.9	8.7	11.0
5 Argentina	66491	32895	33596	8.9	8.9	8.9
6 Haiti	62683	41208	21475	8.4	11.2	5.7
7 Ecuador	27692	13214	14478	3.7	3.6	3.8
8 Spain	16675	9150	7525	2.2	2.5	2.0
9 Brazil	14227	6173	8054	1.9	1.7	2.1
10 United States of America	12323	6421	5902	1.7	1.7	1.6
11 Dominican Republic	11926	4654	7272	1.6	1.3	1.9
12 China	9213	5247	3966	1.2	1.4	1.1
13 Cuba	6718	3484	3234	0.9	0.9	0.9
14 Mexico	5806	2753	3053	0.8	0.7	0.8
15 Germany	5736	2809	2927	0.8	0.8	0.8
16 Other	53451	27758	25693	7.2	7.5	6.8
17 Undeclared country	3482	1848	1634	0.5	0.5	0.4
Total	**746465**	**369142**	**377323**	**100.0**	**100.0**	**100.0**

SOURCE: Department of Foreigners and Migration, Government of Chile and 2018 Census.

Table 13: GINI Coefficient by Region, 2015-2017.

	GINI Coefficient	
	2015	**2017**
I. Tarapacá	0.45	0.40
II. Antofagasta	0.44	0.41
III. Atacama	0.42	0.43
IV. Coquimbo	0.43	0.45
V. Valparaíso	0.44	0.44
VI. O'Higgins	0.44	0.40
VII. Maule	0.44	0.45
VIII. Bío Bío	0.46	0.47
IX. Araucanía	0.48	0.48
X. Los Lagos	0.45	0.46
XI. Aysén	0.45	0.48
XII. Magallanes	0.43	0.45
XIII. Metropolitana	0.48	0.49
XIV. Los Ríos	0.47	0.47
XV. Arica y Parinacota	0.44	0.41
XVI. Ñuble	-	0.46
National	0.48	0.48

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.

Table 14: Characterization of Group 1 Immigrants and Natives, in (ICS) and out of the common support (OSC), specification 4, 2015-2017.

	2015				2017			
	Group 1 ICS	**Natives ICS**	**Group 1 OCS**	**Natives OCS**	**Group 1 ICS**	**Natives ICS**	**Group 1 OCS**	**Natives OCS**
Age	35.9	37.8	39.3	44.0	33.9	37.6	38.7	45.3
Female (%)	46.1	47.2	46.6	41.4	46.2	46.7	46.4	41.8
Schooling	13.0	13.1	11.6	11.5	13.6	13.2	12.9	11.7
Experience	16.9	18.6	21.7	26.5	14.4	18.3	19.8	27.7
Income Poverty (%)	4.4	4.1	7.3	6.2	4.5	3.3	7.0	4.0
Multidimensional Poverty (%)	20.1	14.7	25.1	18.5	19.0	14.7	23.6	17.7
Hourly Wage	3472.4	2934.5	3516.1	2633.5	3260.6	3413.2	3641.2	3019.0
Occupation (%)								
Mangers	4.7	3.4	13.1	5.5	3.7	3.5	8.8	5.3
Professionals	12.9	18.9	7.5	9.4	11.9	17.7	10.0	10.8
Technicians	8.7	7.7	8.8	10.2	8.1	8.4	6.9	11.3
Clerical Support	8.0	7.9	9.4	10.1	6.9	5.8	9.7	8.8
Services and Sales	19.6	19.8	15.2	14.7	27.3	20.0	17.1	14.3
Skilled Agricultural, Forestry and Fishery	0.9	0.6	4.8	5.8	0.8	0.5	3.6	4.4
Craft and Related Trade	16.9	16.6	13.1	12.9	13.7	16.3	9.5	12.8
Machine Operators and Assemblers	4.1	8.2	4.9	9.6	3.5	7.2	5.2	9.8
Elementary	24.3	16.8	23.2	21.2	24.0	20.7	28.6	21.8
Sector (%)								
Agriculture, Hunting and Forestry	1.7	1.5	5.3	10.9	2.9	4.3	5.0	9.7
Fishing	0.1	0.2	0.9	1.1	0.1	0.1	0.9	1.3
Mining and Quarrying	1.5	1.8	2.9	2.9	0.3	0.6	1.6	2.3
Manufacturing	9.0	9.6	7.7	9.6	9.7	10.0	7.4	9.1
Electricity, Gas and Water Supply	0.4	0.1	0.8	0.9	0.1	0.1	0.8	1.0
Construction	11.9	11.1	8.2	8.5	9.3	10.4	9.1	8.4
Wholesale and retail trade	21.4	24.1	17.3	17.4	23.0	24.2	14.0	17.9
Hotels and Restaurants	12.3	5.3	12.0	3.8	13.8	5.7	17.1	3.8
Transport, Storage and Communications	4.2	7.3	5.8	7.9	4.7	6.5	6.4	7.8
Financial Intermediation	1.3	1.3	2.1	2.0	1.0	1.4	3.0	1.7
Real estate	8.0	9.2	5.6	6.3	12.3	9.7	10.8	6.3
Public administration and defence	1.3	1.6	4.3	6.6	0.9	1.9	2.2	6.6
Education	4.5	9.5	4.8	8.1	2.7	7.5	2.3	8.3
Health and Social Work	4.9	6.5	3.5	5.0	4.5	6.0	3.3	5.7
Other	4.8	2.3	8.6	3.4	3.6	3.6	6.0	3.8
Private Households	12.7	8.4	8.7	5.4	10.6	7.8	7.2	5.0

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.

Table 15: Characterization of Group 2 Immigrants and Natives, in (ICS) and out of the common support (OCS), specification 4, 2015-2017.

	2015				2017			
	Group 2 ICS	**Natives ICS**	**Group 2 OCS**	**Natives OCS**	**Group 2 ICS**	**Natives ICS**	**Group 2 OCS**	**Natives OCS**
Age	35.3	37.5	38.0	43.7	33.3	37.3	37.1	45.1
Female (%)	46.5	46.7	49.1	41.9	46.9	46.3	48.4	42.2
Schooling	12.7	13.0	10.8	11.6	13.4	12.9	12.2	11.8
Experience	16.6	18.5	21.3	26.0	14.0	18.2	18.9	27.3
Income Poverty (%)	4.5	4.0	8.9	6.1	4.7	3.4	8.6	4.0
Multidimensional Poverty (%)	23.0	15.1	31.9	18.2	20.5	15.2	27.2	17.4
Hourly Wage	3082.5	2749.7	2635.5	2703.2	2686.5	3118.2	2153.5	3128.9
Occupation (%)								
Mangers	3.0	2.2	8.2	5.7	2.3	2.9	4.8	5.4
Professionals	8.9	16.4	6.5	10.7	9.0	14.2	4.6	12.2
Technicians	8.2	6.4	5.4	10.4	8.0	7.6	6.4	11.4
Clerical Support	7.7	7.8	8.7	10.0	7.3	6.4	9.8	8.4
Services and Sales	19.7	21.2	17.0	14.7	29.1	21.7	19.2	14.0
Skilled Agricultural, Forestry and Fishery	0.9	0.3	6.3	5.5	0.9	0.6	3.7	4.2
Craft and Related Trade	18.9	18.0	15.4	12.8	13.9	17.2	10.8	12.7
Machine Operators and Assemblers	3.8	8.6	6.1	9.4	3.4	7.0	5.6	9.7
Elementary	28.9	19.1	26.4	20.3	26.0	22.6	34.4	21.2
Sector (%)								
Agriculture. Hunting and Forestry	1.7	1.3	5.0	10.3	3.0	4.7	5.3	9.3
Fishing	0.1	0.2	0.7	1.1	0.1	0.1	1.0	1.2
Mining and Quarrying	1.3	1.7	2.9	2.9	0.3	0.7	1.4	2.2
Manufacturing	9.4	10.5	8.2	9.4	9.9	10.6	6.7	9.0
Electricity, Gas and Water Supply	0.2	0.1	0.9	0.8	0.1	0.1	0.9	1.0
Construction	13.2	11.5	6.9	8.6	9.2	10.6	7.0	8.4
Wholesale and retail trade	21.7	25.3	17.7	17.5	24.1	25.9	15.6	17.6
Hotels and Restaurants	13.1	5.9	12.6	3.8	14.5	6.2	18.7	3.8
Transport, Storage and Communications	3.7	7.3	5.0	7.9	4.7	6.0	5.6	7.9
Financial Intermediation	1.1	1.0	2.2	2.0	0.7	0.7	2.5	1.9
Real estate	6.9	8.5	5.2	6.7	11.4	10.6	11.2	6.2
Public administration and defence	1.1	1.7	3.5	6.2	0.5	0.7	1.2	6.8
Education	2.2	7.8	4.2	8.7	1.6	5.4	2.5	8.9
Health and Social Work	4.3	5.1	4.5	5.5	4.2	5.4	2.7	6.0
Other	4.6	2.4	8.0	3.3	3.3	3.6	5.8	3.8
Private Households with Employed Persons	15.4	9.7	11.4	5.3	11.7	8.4	9.0	4.9

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.

Table 16: Characterization of Group 2 Immigrants and Natives, in (ICS) and out of the common support (OCS), specification 1, 2015-2017.

	2015				2017			
	Group 2 ICS	**Natives ICS**	**Group 2 OCS**	**Natives OCS**	**Group 2 ICS**	**Natives ICS**	**Group 2 OCS**	**Natives OCS**
Age	38.4	40.1	44.2	45.5	36.8	40.6	38.0	47.4
Female (%)	50.0	45.4	58.3	39.5	50.1	43.5	56.7	42.5
Schooling	12.2	12.9	9.9	10.5	12.7	13.0	6.3	10.6
Experience	20.2	21.1	28.3	29.0	18.2	21.6	25.7	30.8
Income Poverty (%)	5.0	3.7	13.0	8.3	6.9	2.8	12.3	5.5
Multidimensional Poverty (%)	23.8	14.1	23.9	22.2	20.4	13.7	48.7	22.0
Hourly Wage	3289.3	2953.6	3390.8	2385.2	3057.1	3374.2	4311.4	2732.6
Occupation (%)								
Mangers	4.5	5.0	4.5	5.0	4.8	5.0	6.0	4.5
Professionals	8.3	13.4	34.4	9.9	7.8	14.8	11.0	9.2
Technicians	5.9	11.5	0.0	6.9	4.8	12.1	0.0	7.9
Clerical Support	8.3	12.0	0.0	6.2	6.4	9.3	0.0	5.8
Services and Sales	18.4	17.3	1.7	14.4	27.6	16.5	19.8	14.7
Skilled Agricultural, Forestry and Fishery	1.0	1.7	16.6	8.0	1.5	1.8	18.7	5.9
Craft and Related Trade	17.0	12.8	10.5	15.3	13.7	13.0	8.9	14.9
Machine Operators and Assemblers	5.1	8.8	0.0	9.8	4.3	9.5	2.8	8.4
Elementary	31.5	17.0	32.3	24.2	29.1	17.4	30.3	28.1
Sector (%)								
griculture. Hunting and Forestry	1.0	3.4	3.5	15.2	3.0	4.2	21.2	14.7
Fishing	0.0	0.3	0.0	1.7	0.3	0.6	0.0	1.5
Mining and Quarrying	1.8	2.7	0.0	2.6	0.8	2.1	0.0	1.5
Manufacturing	9.3	10.1	21.8	8.9	9.1	9.8	2.3	8.6
Electricity, Gas and Water Supply	0.2	0.7	0.0	0.6	0.3	0.8	0.0	0.8
Construction	12.5	8.3	3.6	10.4	9.8	8.3	14.1	9.9
Wholesale and retail trade	21.6	20.5	10.7	17.4	19.8	20.3	31.3	18.4
Hotels and Restaurants	11.8	4.4	1.7	3.9	18.2	4.4	4.7	4.3
Transport, Storage and Communications	4.8	8.5	0.0	6.8	4.8	8.0	2.6	6.4
Financial Intermediation	1.9	2.5	0.0	0.9	1.5	2.1	0.0	0.9
Real estate	5.9	9.0	0.0	4.4	6.6	8.8	0.3	4.7
Public administration and defence	1.5	5.5	0.0	5.0	0.7	5.7	2.6	4.7
Education	3.1	8.7	20.1	8.2	2.5	8.3	0.0	7.7
Health and Social Work	4.0	6.2	14.3	4.4	5.3	6.6	11.0	4.6
Other	3.9	3.4	0.0	2.6	3.6	4.3	0.0	3.0
Private Households with Employed Persons	16.3	5.7	24.3	6.9	13.0	4.7	9.9	7.5

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.

Table 17: Characterization of Group 2 Immigrants (cohort 2) and Natives, in (ICS) and out of the common support (OCS), specification 2, 2015-2017.

	2015				2017			
	Group 2 ICS	**Natives ICS**	**Group 2 OCS**	**Natives OCS**	**Group 2 ICS**	**Natives ICS**	**Group 2 OCS**	**Natives OCS**
Age	38.3	38.8	44.0	44.5	36.8	39.0	39.5	45.7
Female (%)	50.4	47.3	42.1	40.3	49.8	45.6	59.5	41.7
Schooling	12.3	13.1	9.2	11.2	12.8	13.2	8.7	11.4
Experience	20.0	19.7	28.9	27.3	18.0	19.7	24.8	28.3
Income Poverty (%)	4.8	3.6	14.4	6.9	6.9	2.6	6.5	4.5
Multidimensional Poverty (%)	23.6	13.8	28.9	19.7	20.3	13.6	30.0	18.9
Hourly Wage	3299.1	3032.5	3042.5	2524.0	3091.2	3482.3	2429.7	2919.6
Occupation (%)								
Mangers	4.2	2.7	12.6	6.3	4.6	4.1	10.2	5.2
Professionals	8.5	17.2	10.7	8.8	8.0	17.5	3.4	9.9
Technicians	6.1	9.7	0.0	9.5	4.5	10.4	10.2	10.6
Clerical Support	8.1	10.5	11.2	9.0	6.3	8.2	5.7	7.8
Services and Sales	18.5	18.9	12.6	14.4	27.7	18.7	21.6	14.1
Skilled Agricultural, Forestry and Fishery	0.9	0.2	8.2	6.9	1.3	0.4	11.4	5.1
Craft and Related Trade	16.7	13.1	21.9	14.3	13.7	13.4	12.6	13.9
Machine Operators and Assemblers	5.0	7.2	6.5	10.4	4.4	7.2	2.5	10.2
Elementary	32.0	20.5	16.3	19.8	29.4	20.2	21.9	22.3
Sector (%)								
Agriculture. Hunting and Forestry	0.9	2.3	4.6	12.0	2.9	3.2	11.8	11.2
Fishing	0.0	0.1	0.5	1.4	0.3	0.2	1.3	1.4
Mining and Quarrying	1.8	2.4	0.2	2.8	0.8	1.8	0.0	1.9
Manufacturing	9.4	9.5	12.4	9.7	9.2	9.7	4.7	9.1
Electricity, Gas and Water Supply	0.2	0.7	1.4	0.6	0.4	0.6	0.0	0.9
Construction	12.4	8.9	10.7	9.4	9.9	8.5	8.2	9.2
Wholesale and retail trade	21.3	20.0	28.3	18.7	19.6	20.8	28.9	18.9
Hotels and Restaurants	11.9	4.5	4.7	4.0	18.3	4.6	12.7	4.2
Transport, Storage and Communications	4.8	7.6	5.5	7.8	4.8	6.9	3.6	7.7
Financial Intermediation	1.9	2.4	0.0	1.5	1.6	2.3	0.0	1.3
Real estate	5.8	9.8	7.7	5.4	6.8	9.9	2.0	5.7
Public administration and defence	1.6	5.2	0.0	5.4	0.7	5.0	0.6	5.5
Education	3.2	9.9	6.3	7.7	2.6	8.8	0.0	7.6
Health and Social Work	4.0	6.3	6.2	4.9	5.4	6.9	2.4	5.2
Other	3.9	3.3	1.2	2.9	3.1	4.4	15.5	3.4
Private Households with Employed Persons	16.6	7.0	10.5	5.7	13.2	5.5	6.6	5.9

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.

Table 18: Characterization of Group 2 Immigrants (cohort 2) and Natives, in (ICS) and out of the common support (OSC), specification 3, 2015-2017.

	2015				2017			
	Group 2 ICS	**Natives ICS**	**Group 2 OCS**	**Natives OCS**	**Group 2 ICS**	**Natives ICS**	**Group 2 OCS**	**Natives OCS**
Age	38.1	38.0	43.7	44.1	36.6	39.0	41.1	45.0
Female (%)	49.9	45.5	54.1	41.8	49.1	45.2	67.2	42.3
Schooling	12.4	12.9	9.5	11.5	12.8	13.0	10.1	11.7
Experience	19.8	19.0	28.2	26.6	17.9	19.9	25.0	27.3
Income Poverty	4.6	3.5	12.4	6.5	6.8	2.8	9.4	4.2
Multidimensional Poverty (%)	23.2	14.5	33.5	18.8	20.3	14.1	26.2	18.1
Hourly Wage	3308.9	2787.5	2997.2	2683.1	3101.8	3199.1	2497.1	3096.4
Occupation (%)								
Mangers	4.6	5.1	3.8	4.9	4.9	5.4	4.0	4.6
Professionals	8.5	12.4	9.6	11.7	7.9	13.1	6.7	12.5
Technicians	6.0	9.4	3.5	9.6	4.7	10.2	6.1	10.6
Clerical Support	8.2	11.5	8.3	8.7	6.4	10.0	4.6	7.1
Services and Sales	18.5	19.5	14.5	14.7	27.8	18.9	22.9	14.5
Skilled Agricultural, Forestry and Fishery	0.9	0.7	5.8	5.9	1.3	0.9	6.9	4.3
Craft and Related Trade	17.1	15.5	13.4	13.2	14.1	14.3	6.6	13.5
Machine Operators and Assemblers	5.1	9.1	4.1	9.3	4.5	8.9	1.7	9.2
Elementary	31.2	16.6	37.0	21.5	28.5	18.1	40.1	23.0
Sector (%)								
agriculture. Hunting and Forestry	0.7	1.2	5.7	11.3	2.9	2.8	8.4	10.5
Fishing	0.0	0.0	0.0	1.3	0.2	0.1	1.5	1.3
Mining and Quarrying	1.6	1.4	3.8	3.1	0.7	0.8	1.3	2.3
Manufacturing	9.7	12.2	6.2	8.6	9.4	11.6	3.8	8.4
Electricity, Gas and Water Supply	0.1	0.1	1.9	0.9	0.2	0.1	2.6	1.0
Construction	12.6	11.1	8.2	8.4	10.1	8.7	6.0	9.0
Wholesale and retail trade	22.0	26.1	13.9	16.4	20.4	28.0	12.9	16.1
Hotels and Restaurants	12.0	5.1	6.7	3.8	18.3	5.7	14.9	3.8
Transport, Storage and Communications	4.6	8.5	8.3	7.4	4.6	7.0	6.2	7.6
Financial Intermediation	1.8	1.5	3.0	1.9	1.4	0.8	2.6	2.0
Real estate	6.1	8.0	2.2	6.7	6.8	10.8	3.8	5.8
Public administration and defence	1.6	2.4	0.7	6.5	0.6	1.0	1.5	7.1
Education	2.9	6.3	10.0	9.4	2.2	5.8	7.1	9.0
Health and Social Work	3.9	5.3	7.2	5.5	5.4	5.8	3.8	5.8
Other	3.8	3.2	4.8	3.0	3.3	3.8	9.1	3.8
Private Households	16.6	7.5	13.6	5.7	13.0	6.6	13.3	5.4

SOURCE: Author's calculations based on CASEN 2015 and CASEN 2017.