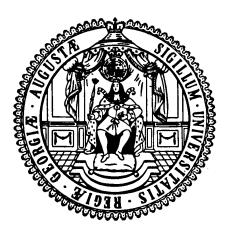
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Adriana Cardozo, Inmaculada Martínez-Zarzoso, Luis R. Díaz Pavez

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Platz der Göttinger Sieben 3 · 37073 Goettingen · Germany · Phone: +49-(0)551-398172 · Fax: +49-(0)551-398173 e-mail: uwia@gwdg.de · http://www.iai.wiwi.uni-goettingen.de

# The Impact of Migration on Wages in Costa Rica

Adriana Cardozo \*

Imaculada Martinez-Zarzoso<sup>†</sup>

Luis R. Diaz Pavez<sup>‡</sup>

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#### Abstract

In recent years, Costa Rica has experienced greater international migration from neighboring countries due to political, economic, and social reasons, raising discussions on the impact of migration on wages of native Costa Rican workers. This paper is the first attempt to disentangle the impact of migration on wages for native Costa Ricans from the impact for migrants. We analyze the effect within groups of education, experience and regions as suggested by the so-called *spatial correlation approach*. Furthermore, we address endogeneity by constructing a shift-share instrument, and heterogeneity by using different sets of fixed effects. Our results show that on average, immigration has no effect on the wages of both natives and migrant workers with comparable skills for the period 2011 to 2019. The outcomes hold when using the *national labor market approach* as well as when changing the panel data estimation strategy. We also find that the effects vary by education level, in particular for high skilled workers a negative and significant effect is shown

Keywords: immigration, wages, labor markets, Costa Rica

JEL Codes: F22, F66, J61, J31

 $<sup>^{*}</sup>$ University of Goettingen

<sup>&</sup>lt;sup>†</sup>University of Goettingen and University Jaume I

<sup>&</sup>lt;sup>‡</sup>University of Goettingen

#### 1 Introduction

In recent years, Costa Rica has witnessed an increasing flow of immigrants from other Central American countries, attracted by the country's growing and stable economy, a solid democracy, and lack of political and civil conflicts. In contrast, its neighboring country, Nicaragua, has suffered from political turmoil, persistent and increasing poverty rates, and the deterioration of economic conditions. These factors have led to greater emigration of Nicaraguans to Costa Rica. Migration opportunities to the US has also decreased, further increasing the number of immigrants to Costa Rica, not only from Nicaragua but also from countries in the Northern Triangle (Guatemala, Honduras and El Salvador). Surprisingly, the impact of this recent migration wave on the Costa Rican labour market has not received much attention in the academic literature, and hence, motivates the subject of this paper.

Existing empirical research on the impact of immigration on wages in destination countries shows, at best, mixed results. As stated by Borjas (2003), competitive labor market models predict a negative effect on wages by natives due to an increase in labor supply. Nevertheless, evidence shows that the impact depends on several factors, like the magnitude of the inflow; whether immigrants are perfect substitutes of native workers due to their skill levels; on labor market rigidities impeding the adjustment of wages; and on the responses of native workers. Moreover, if immigration occurs due to higher labor demand in sectors or destinations with increasing wages and good employment prospects, an expansion of the labor force does not necessarily translate into falling wages (Edo and Rapoport, 2018). For these reasons, the effects of immigration on labour market outcomes is an empirical question and deserves further investigation.

The main novelty of this paper is to investigate whether immigration to Costa Rica has had an effect on wages over the period 2011 to 2019. By using a sound identification strategy and a novel approach, we are able to add further evidence to this question. More specifically, following Edo and Rapoport (2018) and Mayda et al. (2018), this paper uses the skill-cell approach developed by Borjas (2003) augmented with the regional dimension to become a particular type of *spatial correlation* approach. To address endogeneity issues, the approach is improved with the use of a shift-share instrument based on the past settlements of migrants from the same country of origin.

The empirical approach consists of estimating models using this particular type of *spatial correlation* approach, which in simple terms is the estimation of the effect of migration on wages within cells of education-experience-region. We first estimate the effect of migration on the real hourly wages of Costa Rican workers and next focus on the effect of migration on wages of already-established migrant workers. In doing this, we can analyse whether new migrants and resident

migrants have a higher substitutability than new migrants and natives. We find that in both the FE and FE-IV estimations, migration does not show any significant effect on wages of Costa Rican workers. Differently, in the case of resident migrant workers, the FE estimation shows a negative and statistically significant effect of migration on wages, but after controlling for endogeneity, the significance vanishes. These results are validated using the *national labor market approach*, which does not consider the regional dimension to construct the cells. Results also show that there is no effect of migration on wages after controlling for endogeneity. The findings are also robust to estimating the models in first differences (with and without IV).

Even though these findings challenge the results derived from the law of supply and demand, it does not mean that they are unexpected. Several theoretical explanations help to rationalize these findings. First, there could be complementary skills between recently arrived migrants and workers in Costa Rica with comparable skills (Peri and Sparber, 2010; Ottaviano and Peri, 2012; Dustmann et al., 2016). Second, there could be a change in the specialization of workers in Costa Rica as a rational response to migration, in which some workers move from jobs that are intensive in manual tasks to better paid jobs that are intensive in communication intensive tasks (Peri and Sparber, 2009). Third, there could be an increase in the production of goods that are more intensive in the now more abundant skill (e.g low-skilled workers), thus, generating an increase in demand for these workers (Rybczynski, 1955). Finally, there could be an uptake in technology adoption towards one that is more intensive in the now more abundant skill, increasing their marginal productivity and wages (Beaudry and Green, 2005). From an empirical point of view, our results are in line with the existing literature. For instance, using a different approach and a different survey, Gindling (2009) also found an overall zero effect of migration on wages of native workers in Costa Rica for the period 1997-2004.

From a methodological point of view, and according to Abadie (2020), it is important to report findings showing non-significant effects, since they bear relevant information that could be even more valuable than the expected significant effects <sup>1</sup>. This would be particularly true in empirical contexts like the one in our setting, with large data sets and some theoretical and empirical evidence that suggests the absence of the expected effect.

The remainder of the paper is organized as follows. Section 2 presents a brief literature review summarising the outcomes of related papers on the impact of migration on wages. Section 3 describes the data and variables used in the Costa Rican context. Section 4 outlines the empirical strategy and the main results are presented and discussed in Section 5. Finally, Section 6 concludes

<sup>&</sup>lt;sup>1</sup>More specifically, through a calibration of posterior probability functions using data from Economics Laboratory Experiments, Abadie (2020) shows that the rejection of a typical null hypothesis often carries little information, while failure to reject is highly informative.

with a summary of the main findings and a few suggestions for further research.

#### 2 Literature review

This section begins by summarizing the general studies focusing on the theoretical and empirical effects of migration on wages. Next, two subsections focus on more specific research that covers the heterogenous effects of migration (2.1) and the empirical evidence for Latin American countries (2.2).

From a theoretical point of view, one should expect that the effect of migration on wages follow the laws of supply and demand. In this case, an increase of immigration is the equivalent to a supply shock, followed by a decrease in wages. However, empirical research on this topic usually finds that immigration does not affect wages. Plausible explanations for the findings of this zero effect are linked to the related theories and methodologies. First, migrants and natives are not perfect substitutes as usually assumed in the theoretical explanations. Specifically, there could be differences in educational levels between them, or there could be complementary skills for workers with the same educational level (Peri and Sparber, 2010; Ottaviano and Peri, 2012; Dustmann et al., 2016). In addition, according to Peri and Sparber (2009) a migration inflow would induce native workers to move from manual tasks to communication intensive tasks as a rational response in order to avoid competitive pressures on wages. This would in turn offset the expected negative effect, as shown by empirical evidence found for the US (Peri and Sparber, 2009) and Spain (Amuedo-Dorantes and De La Rica, 2011). Second, according to the Rybczynski theorem (Rybczynski, 1955), a migration inflow would generate a change in the output mix via a relative increase in the output of the sectors using the now more abundant skill intensively (e.g. textiles if there is a shift toward more low-skilled workers). This change in the output mix would keep wages constant via an increase in the demand for these workers generated by an increase in the supply of its output. Beyond the effect on the output mix, a complementary phenomenon would be the impact of migration on technology adoption. Specifically, firms would change their technology towards one that is more intensive in the now more abundant skill. Therefore, and according to Beaudry and Green (2005), some firms would begin to use relatively more manual tasks, and therefore, they would adopt technology that is complementary to these workers, increasing their marginal productivity and then their wages. Empirical evidence supporting the effect on the output mix and on the technology adoption hypotheses have been reported for the US by Hanson and Slaughter (2002); Lewis (2005) and Beaudry et al. (2010), for Spain by Gonzalez and Ortega (2011), and for Germany by Dustmann et al. (2013).

From a methodological perspective, immigration-driven supply shocks may be endogenous. According to the literature, there are two main sources of endogeneity. The first source is reverse causality, since immigrants could sort themselves to job positions or regions with higher wages (Dustmann et al., 2005; Llull, 2018), this phenomenon is also known as endogeneity of immigrants's location choices. Second, native workers could respond to migration by acquiring greater skills and moving into other local labor markets with higher wages ((Borjas, 2006; Ortega and Verdugo, 2016). This phenomenon is called the *diffusion* effect. These two endogeneity sources may explain why wages do not decrease and could even rise, although the labor supply is increasing, making it difficult to find a causal effect of migration on wages.

There are two main econometric approaches for dealing with the endogeneity issues. To solve the endogeneity of local labour market conditions Card (2001) proposes the shift-share instrumental variable methodology in the context of *spatial correlation*. This approach consist of creating an instrumental variable that interacts the regional distribution of previous immigrants from each country of origin (share component) and the time varying inflow of immigrants from those countries at the national level (shift component). The second econometric approach is the *national labor market* one proposed by Borjas (2003), who considers the effect of migration in every skill cell of education-experience at the national level.

It is very important to clarify that these two empirical strategies capture the direct partial effects of immigration on wages in the short run. The *national labor market approach* considers workers with comparable skills, whereas the *spatial correlation* approach considers workers with similar skills within the same region. Results using both approaches separately lead to diverging results, with the skill-cell approach mainly showing a negative effect of immigration on average wages and the *spatial correlation approach* leading to zero effects. Edo and Rapoport (2018) and Borjas and Monras (2017) combine both approaches and, while the former finds a relatively small negative effect on wages of native workers with comparable skills for the US with annual data from 2000 to 2013, the latter finds a big negative wage elasticity of -1.3, mainly driven by low-skilled workers in a replication of the Marielitos study.

#### 2.1 Substitutability between workers and heterogenous effects by skill level

As argued before, the short-term effects of immigration on wages of workers in the host country depends on the substitutability or complementarity of native workers with immigrants. On the one hand, some immigrants and workers could be substitutes because they have similar or similarly perceived skill levels (in the case of migrant downgrading) and hence, they compete for the same jobs. Consequently, a migration-driven increase in labor supply would depress native wages for that skill level. On the other hand, new immigrants and domestic workers could be complements in some cases. A decrease in the cost of a low-skilled activity, like construction, would generate an increase in production and thereafter an increase in demand for high-skilled construction workers, such as electricians, and for high-skill related activities, such as professional air conditioning installation. The heterogeneous effect of migration would thus depend on the skill level of migrants and native workers. For example, in the UK, Nickell and Saleheen (2015) find a small negative impact on average British wages using annual data for the period 1992-2014. Ruhs (2018) find that an increase of 1% in EU immigration leads to a 0.8% decrease in wages of UK-born workers at the 5th and 10th percentiles of wages and a 0.6% increase for the 90th percentile. In contrast, using yearly data for the years 1997-2005 Dustmann et al. (2013) find a slightly positive average effect. Nevertheless, these estimations only show a short-run response to migration, which according to Ruhs (2018) is expected to vanish over time. Considering the substitutability issue, Ottaviano and Peri (2012) used, in their estimations, the elasticity of substitution derived from a structural labor demand function for the period 1990-2006 in the US and concluded that immigration to the US had a modest negative long-run effect on real wages of less educated natives.

Hence, if there is no significant effect of migration on the wages of native workers due to the imperfect substitutability between migrants and native workers, one should expect that there could be an effect on already established immigrant workers. In particular, new migrants are likely to be closer substitutes for the skills of migrants already employed. Manacorda et al. (2012) tested this reasoning with data from the UK for the period 1975-2005 using age-education cells. They found that immigration had a negative effect on the wages of resident migrant workers relative to natives. The effect was concentrated among university-educated migrants, who suffered a deterioration in their returns to education due to competition from equally highly-educated recent arrivals, while native workers did not suffer this deterioration in wages because of the low level of substitutability with immigrants.

#### 2.2 South-south migration: Empirical evidence for Costa Rica and Colombia

In this section, we focus on two studies with methodological similarities to our work: Gindling (2009) and Caruso et al. (2019), as there are only few studies that analyze empirically the effect of migration on wages in Latin American countries.

The former uses the *national labor market* approach to analyze the effect of Nicaraguan migration on the wage structure of Costa Rican workers. Although there was no evidence of a significant effect on average Costa Rican earnings, the authors find a negative and slightly significant effect (significant only at 10% level) for Costa Rican women who did not finish primary education and a positive and significant effect for Costa Rican women with completed secondary education. According to these findings, the author states that for the first group of women, migrants are substitutes while for the second, they are complements. However, that work does not account for the endogeneity of immigrants' location choices and second, the panel structure is made with irregular year gaps as they used the years 1997, 2000, 2001, 2003 and 2004. Therefore, important information about the variation of Nicaraguan migration in each skill-cell and of wages within these skill-cells is missing for some years. In contrast, our work accounts for the endogeneity problem; uses a longer and regular time period; considers migration from all the origin countries, and is based on a labor survey rather than a household survey, which gives us a more representative sample in terms of labor market outcomes.

Caruso et al. (2019) analyze the effect of Venezuelan migration on wages in Colombia. The authors use the *spatial correlation* approach with a a shift-share instrument accounting for the distance between each Venezuelan province and the Colombian departments where immigrants arrive. This study finds a sizable short-term negative and statistically significant effect on Colombian informal sector workers living in urban areas. Particularly, a 1-percentage point increase in Venezuelan immigration is associated with a 10-percentage point reduction in wages for these workers. According to the authors, this occurs through occupational downgrading of native workers, because once migrants enter the labor market, natives are only able to get jobs in activities below their qualifications. However, this result does not take into account the diffusion effect derived from natives eventually moving to locations with better job prospects.

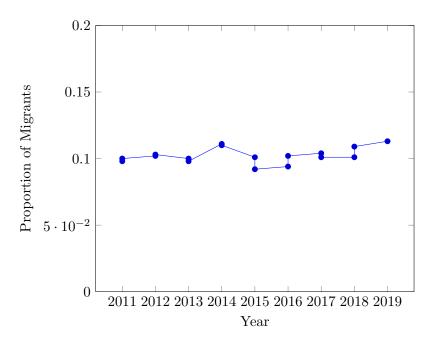
Considering the Costa Rican labor market, characterized by market imperfections, high informality and high wage inequality, we infer that both the *national labor market* and the *spatial correlation* approach need to be used jointly in order to minimize any source of endogeneity generated by the fragile structure of these labor markets. For instance, one could expect a stronger native flight response to migration in light of the high share of precarious jobs and low wages, since migrant workers would be ready to work for an even lower wage than natives, creating large incentives for the latter to look for opportunities in wealthier regions. On the other hand, we could expect the endogeneity of migrants' decisions to be present as well due to the high concentration of migrants in certain regions, like the northernmost Huetar Norte, which has a high concentration of Nicaraguan migrants due to its proximity to Nicaragua (24.08% of migrants lived in Huetar Norte in the 2019). Therefore, in order to obtain a consistent estimator of the wage effect of migration for a country like Costa Rica, both endogeneity issues of immigrants' location choices and the diffusion effect must be considered. In this work, we use the combination of both approaches in the line of Jaeger et al. (2018), Peri (2012) and Borjas (2014), who refer to this combination as a particular type of spatial correlation approach, denomination that we adopt in this paper.

#### **3** Data and descriptive statistics

We exploit data from the ECE (Encuesta Contínua de Empleo), a labor survey conducted every quarter, covering the period 2011-2019, which provides us with labor characteristics of the Costa Rican population for 33 quarters. The ECE is a continuous labor survey, constructed as a rotating panel, that measures employment throughout the year. The main purpose of the survey is to collect seasonal data on the main labor market indicators (INEC, 2010). The survey mainly targets the working-age population.

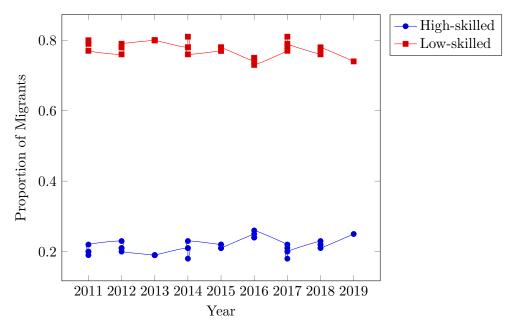
The proportion of migrant workers in Costa Rica remained stable over the period 2011-2019, which oscillated between 9.2% and 11.3% of the total workforce. After a peak of 11% in 2014, the proportion of migrants gradually decreased until the end of 2015, reaching by then the smallest value observed in the period (9.2%). Thereafter, a continuously smooth increase began until the share approached 11.3% by the first quarter of 2019 (Figure 1).

Figure 1: Proportion of Migrant workers over the total labor force of Costa Rica



The majority of migrant workers come from Nicaragua. The proportion is rather stable, increasing from 85.4% in the first quarter of 2011 to 88.3% in the first quarter of 2019, the final period in our sample. Other important countries of origin, ordered by the average proportion of immigrants in the whole period, are Panama(3.7%), Colombia (1,7%), El Salvador (1,3%), Honduras (0,9%) and the United states (0,9%). All remaining countries, accounting for 3,9% of total immigrants, are grouped in a single category. Workers with less than a secondary education are grouped as low-skilled workers (high school dropouts and lower) and account for at least three-quarters of the immigrant population (Figure 2). Regarding the maximum educational attainment of these workers, about 30% did not complete primary education, 26% completed primary education and 22% report having not completed secondary education, with a slight increase in overall educational attainment of immigrants over time. With respect to high-skilled migrants, we observe a clear increase in the proportion of immigrants in the category of those who completed secondary school, from 10.3% to 14.7% over the whole period. Similarly, the share of immigrants who completed a university education increased from 7% to about 9%, while the share of immigrants who did not complete university changed from 1.5% to 2.4%.





The low skill level of the average immigrant contrasts with the average skill level of the native population. Among natives, the share of high-skilled workers increased from 41% to 49% over the study period.

Another important aspect to consider is the evolution of real hourly wages. As shown in Figure 3 there is a systematic difference between real hourly wages of natives and immigrants. Costa Ricans have a 47% higher average real hourly wage compared with immigrants. In addition, we can observe that the real hourly wages have been increasing over time with a similar pattern among regions (not shown in the Figure).

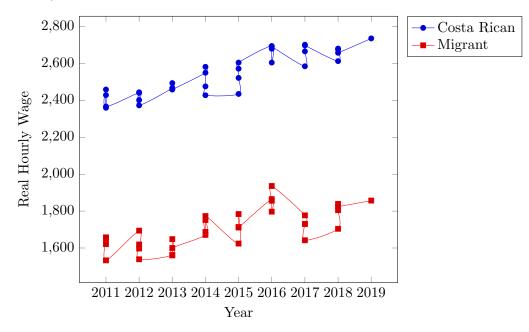


Figure 3: Real hourly wage of Migrant and Costarican workers (In local currency: Costa Rican Colón)

In our data, educational levels are divided into 6 categories: primary incomplete, primary complete, secondary incomplete, secondary complete, university incomplete, and university complete. We define the variable *years of experience* as the time elapsed since the individual finishes her educational process. Considering that Costa Ricans usually begin primary school at the age of 6, this variable equals actual age minus years of education minus 6. We calculate years of experience for individuals aged 16 to 64 years, and exclude from the sample workers with more than 40 years of experience. Once having individual labor market experience, we create 8 groups based on five-year intervals of work experience in order to consider that individuals with almost the same years of experience are likely to influence labour market opportunities of their peers (Welch, 1979). Regarding the regions, we consider the six Costa Rican administrative areas: Central, Chorotega, Pacífico Central, Brunca, Huetar Caribe and Huetar Norte. Therefore, our panel consists of 288 (6\*8\*6) education-experience-region groups over 33 quarters (2011-2019), for a total of 9,504 observations.

Analysis using composite groups of education-experience-region presents some advantages in comparison with using only education-region groups. For example, when analysing a supply shock generated by an increase in low-skilled migrants, we need to take into account how the distribution of work experience in the immigrant population contrasts with that of natives. In this case, considering a region with a high influx of migrants, only a particular segment of natives with tertiary education would be affected if all new immigrants with a similar education were young and hence, had limited experience. In contrast, a completely different segment of natives with the same educational level would be affected if the new migrants were around 50 years old and in general, with greater experience. Our target variable is constructed as the ratio of migrants with respect to the total population for each education-experience-group for two subsamples: For native Costa Rican workers and for settled migrant workers. For the former, we only include Costa Rican workers, while for the latter, we considers migrant workers who have been living more than one year in Costa Rica. More specifically, let us consider a group of workers who have educational level i, experience level j, lives in region r and is observed in quarter t. The measure of the immigrant supply shock for this skill group is:

$$p_{ijrt} = \frac{M_{ijrt}}{M_{ijrt} + C_{ijrt}} \tag{1}$$

where  $M_{ijrt}$  represents the number of immigrants of the specific cell (i,j,r,t) and  $C_{ijrt}$  represents the number of native Costa Rican workers. This expression represents the immigrant share of the labor force in a concrete education-experience-region group in a given quarter. As a dependent variable, we use the average of logged hourly wage of each group of education-experience-region of the two subsamples of native Costa Rican workers and settled migrant workers. To calculate the averages, we consider the hourly gross wage of the first and second main jobs, deflated by the consumer price index using 2016 as the base year (IMF, 2019). The hourly gross wage is constructed by dividing the monthly gross wage by 4 and then by the amount of weekly hours worked. In addition, to reduce the influence of outliers, we exclude from the sample workers with more than 72 weekly working hours and with real hourly wages higher than 40,000 colones, values that are implausible for an average worker in Costa Rica. We only consider workers that participate in the labor force, are not enrolled in school and are not self-employed.

The average of logged hourly wage of the whole sample of workers (including both Costa Ricans and migrants) belonging to some selected education-experience groups<sup>2</sup> in the Central region are shown as an example for descriptive purposes in Table 1. Notice that as expected, for every educational level, the average of logged hourly wage is higher the higher the work experience. In addition, the average of logged hourly wage of every skill group slightly increased over time. Finally, we observe significant variation in wages by education level. For example, the average of logged hourly wage of the skill group of workers who completed primary education and years of experience in the interval 21-25 was 7.26 in 2019, while for the group of workers who completed a university education with the same years of experience was equal to 8.62 in the same year. This variation in wages by education and experience level support our argument for considering them as separate labor markets, reinforcing the choice of our empirical strategy. A similar pattern is observed for the

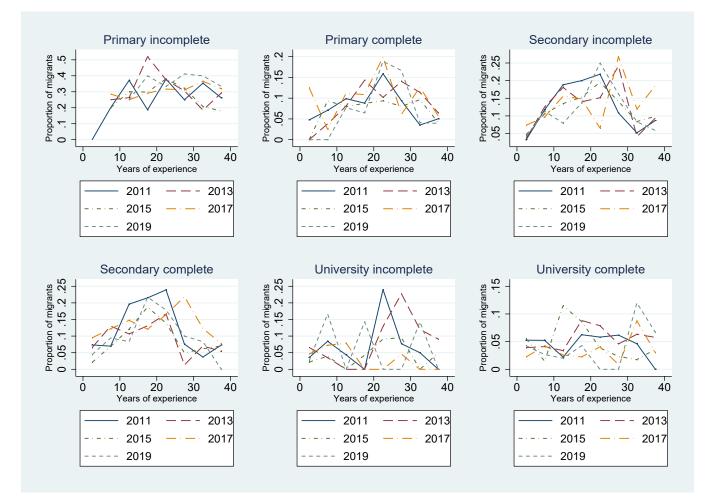
<sup>&</sup>lt;sup>2</sup>We consider only Primary Complete, Secondary Complete and University Complete in the table

other five regions of Costa Rica, also when observing results for Costa Rican and settled migrant workers respectively.

Educational level	Years of experience	2011	2012	2013	2014	2015	2016	2017	2018	2019
Primary Complete	1-5	6,40	6,71		6,73		6,96	7,04	7,38	6,81
r mary Complete				6,58		6,87				
	6-10	7,05	7,02	6,96	6,88	6,97	7,10	7,08	7,05	7,05
	11-15	7,21	7,02	7,10	7,06	7,17	7,22	7,13	7,18	7,13
	16-20	$7,\!10$	7,05	7,16	$7,\!18$	$7,\!18$	7,22	7,25	7,23	7,20
	21-25	$7,\!16$	$7,\!20$	$7,\!20$	$7,\!15$	$7,\!20$	$7,\!23$	$7,\!26$	$7,\!25$	7,26
	26-30	$7,\!21$	$7,\!12$	$7,\!15$	$7,\!17$	$7,\!21$	$7,\!19$	$7,\!23$	$7,\!25$	$7,\!15$
	31 - 35	$7,\!15$	$7,\!16$	7,07	$7,\!17$	$7,\!26$	7,21	$7,\!28$	$7,\!25$	7,22
	36-40	$7,\!15$	$7,\!16$	$7,\!10$	$7,\!14$	$7,\!19$	$7,\!20$	$7,\!19$	$7,\!23$	$7,\!22$
Secondary Complete	1-5	$7,\!19$	$7,\!18$	$7,\!20$	$7,\!19$	$7,\!20$	$7,\!28$	$7,\!29$	$7,\!28$	$7,\!29$
	6-10	$7,\!39$	$7,\!36$	$7,\!35$	$7,\!34$	$7,\!34$	$7,\!38$	$7,\!38$	7,39	$7,\!40$
	11-15	$7,\!53$	$7,\!44$	$7,\!45$	$7,\!48$	$7,\!45$	$7,\!50$	7,46	$7,\!47$	$7,\!47$
	16-20	$7,\!54$	$7,\!53$	$7,\!54$	$7,\!57$	$7,\!54$	$7,\!54$	$7,\!58$	$7,\!54$	$7,\!54$
	21-25	$7,\!56$	$7,\!60$	$7,\!58$	$7,\!60$	$7,\!64$	$7,\!65$	$7,\!62$	7,58	$7,\!59$
	26-30	$7,\!62$	$7,\!61$	$7,\!63$	$7,\!66$	$7,\!56$	$7,\!59$	$7,\!63$	$7,\!64$	$7,\!62$
	31-35	7,72	7,72	7,72	$7,\!66$	$7,\!68$	$7,\!66$	$7,\!64$	$7,\!62$	$7,\!53$
	36-40	7,70	$7,\!85$	7,85	$7,\!82$	7,75	7,78	7,79	7,72	$7,\!62$
University Complete	1-5	8,02	$7,\!99$	$7,\!95$	7,96	8,04	7,96	$7,\!95$	8,01	$^{8,00}$
* <u>-</u>	6-10	$^{8,25}$	8,24	8,21	$^{8,19}$	$^{8,17}$	8,21	$^{8,23}$	$^{8,19}$	$^{8,27}$
	11-15	8,37	8,37	8,37	8,36	$^{8,37}$	8,41	8,41	$^{8,43}$	8,41
	16-20	8,42	8,48	8,47	$^{8,43}$	$^{8,46}$	$8,\!54$	8,48	$^{8,54}$	8,56
	21-25	$^{8,46}$	$^{8,55}$	$^{8,55}$	$^{8,54}$	$^{8,54}$	$^{8,67}$	$^{8,59}$	$^{8,58}$	$^{8,62}$
	26-30	$^{8,47}$	$^{8,49}$	$^{8,55}$	$^{8,50}$	$^{8,57}$	$^{8,64}$	$^{8,65}$	$^{8,60}$	$^{8,65}$
	31-35	$^{8,63}$	$^{8,51}$	8,56	$^{8,51}$	$8,\!58$	8,67	8,54	$^{8,65}$	8,49
	36-40	8,45	8,47	8,51	8,55	8,62	8,68	8,64	8,59	8,58

Table 1: Average log hourly wage of selected education-experience groups in the region Central

With respect to our target variable, Figure 4 shows that for the whole sample (including both Costa Rican and settled migrant workers) in the Central Region, there is substantial variation over time in the proportion of migrants in each educational group depending on the years of experience. The same pattern can be observed for the other 5 regions of Costa Rica and for the specific proportions in both subsamples of Costa Rican and settled migrant workers. This evidence, together with the information of Table 1, shows that there is substantial variation among education-experience-region groups in both the dependent and target variables.



Before moving to the model specification, we show in Figure 5 simple correlations between the variables of interest. The scatter diagram illustrates the relationship between the quarterly change in the proportion of migrants and the quarterly change in logged hourly wages for our sample of education-experience-region groups of both Costa Rican and already settled immigrant workers. The resulting negative relationship, which shows the correlation between the variables, will be tested in the following section to disentangle the potential causal effect, after controlling for different types of unobserved heterogeneity and endogeneity.

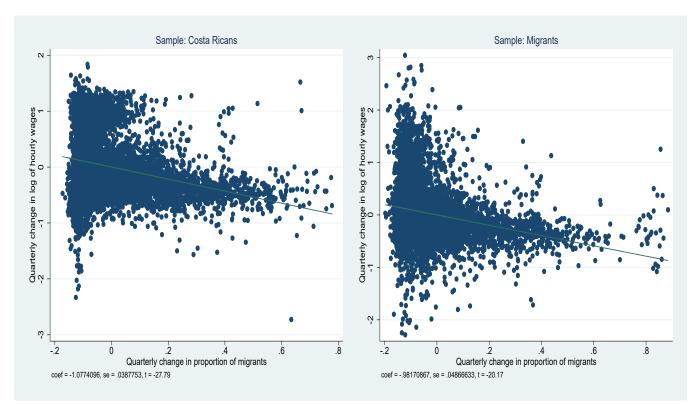


Figure 5: Scatter diagram relating changes in wages and immigration in Costa Rica, 2011-2019

Note: Values plotted correspond to residuals from regressions of the logged hourly wage and of the immigrant share on vectors of education-experience-region fixed effects, quarter fixed effects, education-year fixed effects, experience-year fixed effects and region-year fixed effects. These residuals give the log wage or the immigrant share in the specific education-experience-region-quarter cell relative to that group's mean over the sample period, after removing time effects.

#### 4 Model specification and empirical strategy

The main modelling strategy is based on Borjas (2014), Jaeger et al. (2018) and Edo and Rapoport (2018) who proposed a variant of the already mentioned *spatial correlation* approach for analysing the effect of migration on wages within cells of education-experience-region.

Our baseline model specification takes the following form:

$$y_{ijrt} = \beta_0 + \beta_1 p_{ijrt} + \sigma_{ijr} + \phi_t + \gamma_{iyear} + \theta_{jyear} + \lambda_{ryear} + \epsilon_{ijrt}$$
(2)

where  $y_{ijrt}$  being real hourly wage and  $p_{ijrt}$  the proportion of migrant workers over the total labor force of a specific cell of education-experience-region given by equation 1. In order to control for the different kinds of unobserved heterogeneity (in the form of omitted variable bias) that could bias our estimator, we include different types of fixed effects: Education-experience-region fixed effect ( $\sigma_{ijr}$ ), quarter fixed effect ( $\phi_t$ ) as well as the time-varying fixed effect of education ( $\gamma_{iyear}$ ), experience ( $\theta_{jyear}$ ), and region ( $\lambda_{ryear}$ ). Every regression is weighted by the average quantity of workers belonging to each group of education-experience-region. Moreover, at the time of creating the groups, every worker from the original sample was weighted according to the weighting factor of the survey. In each specification, the standard errors are clustered by group cells in order to control for possible autocorrelation and heteroskedasticity. Finally, in order to avoid a problem of overfitting because of excessive fixed effects, we consider years instead of quarters when computing the interactive time-varying fixed effects.

Even if we are controlling for unobservable heterogeneity with the battery of fixed effects, there is still an endogeneity problem in our model that has to be addressed. In particular, the decision to migrate could be endogenous to the migrant, in the sense that they could migrate to the regions where higher wages are offered. Therefore, we are facing a reverse causality issue that could generate bias in the estimated coefficients in equation 2.

There are several approaches to deal with this endogeneity in the literature. The most popular is the shift-share instrument (also known as the past settlement instrument) proposed by Card (2001) and used in different settings, e.g. Cortes (2008), Peri (2012) and Borjas (2014). We generate an instrument in line with Jaeger et al. (2018). We exploit the fact that immigrants may settle near previous immigrants from the same country of origin. Native workers may behave similarly, since the native workers in a specific skill-region group may not be exogenous to current economic effects of immigration, and therefore may internalize the labor market effects of migration moving to other regions, as is well documented in Peri and Sparber (2010) and Edo and Rapoport (2018). In other words, we use this approach to control for the immigrants' choice decision and the subsequent natives' response. To construct the instrument, we consider the six most common nationalities of migrants in Costa Rica (Honduras, Nicaragua, Panama, El Salvador, Colombia and the US) and create an additional category which groups the remaining countries of origin. Hence, our instrumental variable takes the following form:

$$\tilde{p}_{ijrt} = \frac{\tilde{M}_{ijrt}}{\tilde{M}_{ijrt} + \tilde{C}_{ijrt}}$$
(3)

where,

$$\tilde{M}_{ijrt} = \sum_{c=1}^{C} \frac{m_{ijr}^c (1stquarter2011)}{m_{ij}^c (1stquarter2011)} * m_{ijt}$$
(4)

In equation 4,  $m_{ijr}^c(1stquarter2011)$  represents the number of immigrants of the education-experience group (i,j) in region r from country c in the base period;  $m_{ij}^c(1stquarter2011)$  is the number of immigrants of the same education-experience group present in the whole country in the base period; and  $m_{ijt}$  is the number of migrants of the same education-experience group present in the whole country coming from country c in the specific quarter t. We then sum these shift-share variables for the different origins. For this, we consider the migrants from Nicaragua, Colombia, El Salvador, Honduras, Panama, the United States and an additional group with the remaining countries of origin. We also create a shift-share component for Costa Rican workers, which is defined as:

$$\tilde{C}_{ijrt} = \frac{c_{ijr}(1stquarter2011)}{c_{ij}(1stquarter2011)} * c_{ijt}$$
(5)

Here,  $c_{ijr}(1stquarter2011)$  represents the number of natives of the education-experience group (i,j) living in region r in the base period;  $c_{ij}(1stquarter2011)$  represents the quantity of natives of the same education-experience group present in the whole country in the base period; and  $c_{ijt}(1stquarter2011)$  represents the quantity of natives of the same education-experience group living in the whole country in the specific quarter t. We estimate this new model using a Second-Stage Least Squares estimator (2SLS), where the first and second stages take the following form, First stage:

$$\hat{p}_{ijrt} = \beta_0 + \beta_1 \tilde{p}_{ijrt} + \sigma_{ijr} + \phi_t + \gamma_{it} + \theta_{jt} + \lambda_{rt} + \epsilon_{ijrt}$$
(6)

Second stage:

$$y_{ijrt} = \beta_0 + \beta_1 \hat{p}_{ijrt} + \sigma_{ijr} + \phi_t + \gamma_{it} + \theta_{jt} + \lambda_{rt} + \epsilon_{ijrt}$$
(7)

Additionally, in order to differentiate the effect by the immigrants' skill level, we split our explanatory variable into two: One representing the share of high-skilled immigrants in each educationexperience-region cell and the other representing the share of low skill immigrants in the same cell. In each case, workers who at least finished high school are considered high-skilled and the rest as low-skilled. In line with Mayda et al. (2018), we also constructed an instrumental variable for high-skilled and low-skilled workers respectively and we proceed to instrument them separately. Therefore, the second-stage regression turns into:

$$y_{ijrt} = \beta_0 + \beta_1 \hat{p} h_{ijrt} + \beta_2 \hat{p} l_{ijrt} + \sigma_{ijr} + \phi_t + \gamma_{it} + \theta_{jt} + \lambda_{rt} + \epsilon_{ijrt}$$

$$\tag{8}$$

We test for the validity of our instrumental variable approach by examining the results of the first stage estimations in each estimated model. More specifically, we check the actual correlation of the instrument with the explanatory variable of interest, as well as the value of the F-test robust to autocorrelation and heteroskedasticity. As we can observe in the first stage estimates of the sample for Costa Rican workers in Table A.2.1, the coefficients of the different past settlement instruments are positive and statistically significant for the proportion of immigrants, proportion of high-skilled immigrants, and proportion of low-skilled immigrants, and the F-test is higher than 10 for our basic past Settlement instrument (48.92) and for the past Settlement instrument of low-(525) and high-skilled (134) workers as well, hence, we confirm their relevance. Furthermore, for the sample of immigrant workers, we found similar results, which are shown in Table 3.

Regarding the exclusion restriction, in order to fulfill it, our instrumental variable should only affect real hourly wages through its effect on the proportion of migrants. It means that past immigrants should have to chose destination places following specific labor demand shocks that do not have any long-run persistence in our study period of 8 years. Hence, the critical assumption of our instrumental variable approach is that in an 8-year period any long-run persistence of labor demand shocks should vanish.

## 5 Main results

The main results are shown in Tables 2 and 3. Table 2 shows the effects of migration on the wages of Costa Rican workers, whereas Table 3 refers to the effects on already established migrants. Columns 1 to 4 show the results for the baseline specification in Equation 2 for all educational groups (columns 1 and 2) and also after splitting into high- and low-skilled groups (columns 3 and 4). In each case, we estimated the equation with fixed effects (FE) and in first differences (FD). Overall, the results in Table 2 do not show any statistically significant effect of migration on wages of Costa Rican natives. This holds for average migration and also for migration split into high- or low-skilled immigrants. Columns 5 to 8 show results when addressing endogeneity using the instrumental variable approach. Coefficients remain non-statistically significant for average migration. The only significant effect is that of low-skilled migration (column 7), which is positive and statistically significant at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\mathbf{FE}$	FD	$\mathbf{FE}$	FD	IV-FE	IV-FD	IV-FE	IV-FD
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Proportion of Migrant workers	0.005	0.002			0.089	0.007		
	(0.028)	(0.035)			(0.063)	(0.086)		
Proportion of High skill migrants			0.035	0.021			-0.003	-0.091
			(0.048)	(0.061)			(0.130)	(0.194)
Proportion of Low skill migrants			-0.008	-0.006			$0.128^{*}$	0.045
			(0.034)	(0.042)			(0.070)	(0.093)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education <sup>*</sup> Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region <sup>*</sup> Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9063	8626	9063	8626	8957	8550	8957	8550
R-squared	0.132	0.0168	0.132	0.0168	0.133	•	0.131	•

Table 2: Estimations of the Impact of Migration on Wages of Costa Rican Workers (Group ID: education-experience-region)

Note: \*\*\* stands for significant at the 0.01 level, \*\* at the 0.05 level and \* at the 0.1 level. Robust SE in parenthesis.

Table 3 shows the results obtained when the models are estimated using the wages of already established migrants as a dependent variable. The coefficients in columns 1 (FE) and 2 (FD) are negative and statistically significant. Similarly, as shown in column 3 (FE), the coefficients of highand low-skilled migration are negative and statistically significant, while the same holds only for low-skilled migration in the first differences model (column 4). The magnitude of the coefficient is -0.16, significant at the 5% level (FE column 1) for all migrants, whereas it is higher for highskilled migrants (-0.32) than for low-skilled (-0.11), both significant at the 10% level (FE, column 3). However, as is shown in columns 5-8, none of the coefficients are statistically significant any longer after addressing the endogeneity problem using instrumental variables. It is important to note that the coefficients of the FD specification (columns 2, 4, 6 and 8) show a similar pattern.

Table 3: Estimations of the Impact of Migration on Wages of Migrant Workers (Group ID: education-experience-region)

	(1)	(2)	(0)	(4)	(=)	(0)		(0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\mathbf{FE}$	$\mathrm{FD}$	$\mathbf{FE}$	$\mathrm{FD}$	IV-FE	IV-FD	IV-FE	IV-FD
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Proportion of Migrant workers	-0.160**	-0.237***			-0.058	-0.105		
	(0.066)	(0.081)			(0.187)	(0.227)		
Proportion of High skill migrants			-0.322*	-0.243			-0.102	0.079
			(0.193)	(0.264)			(0.820)	(1.032)
Proportion of Low skill migrants			$-0.117^{*}$	-0.235***			-0.049	-0.137
			(0.065)	(0.078)			(0.136)	(0.198)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region <sup>*</sup> Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5718	4531	5718	4531	4361	3707	4361	3707
R-squared	0.0464	0.0289	0.0465	0.0289	0.0614		0.0615	

# 5.1 Robustness checks: National labor market approach and heterogeneous effects by educational level

As a first robustness check, we estimated our main model (2) as well as the model with the split target variable using the *national labor market* approach of Borjas (2003). This model considers education-experience groups omitting the regional dimension. One drawback of this approach is that we cannot use the regional past settlement instrument since migrants are considered to be spread equally among education-experience groups across the Costa Rican labor market. The results obtained are not very different from those of the *spatial correlation* approach. The estimated coefficients and corresponding standard errors indicate that there is no statistically significant effect of any type of migration neither on Costa Rican workers nor on migrant workers as shown in tables 4 and 5, respectively.

Table 4:	Estimations	of the	Impact	of	Migration	on	Wages of	Costarican	Workers	(Group	ID:
education	n-experience)										

(1)	(2)	(3)	(4)
$\mathbf{FE}$	$\mathbf{FE}$	IV-FE	IV-FE
b/se	b/se	b/se	b/se
-0.012	0.001		
(0.069)	(0.068)		
		-0.015	0.056
		(0.089)	(0.135)
		-0.010	-0.024
		(0.089)	(0.077)
Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes
1558	1505	1558	1505
0.451	0.0800	0.451	0.0803
	FE b/se -0.012 (0.069) Yes Yes Yes 1558	FE       FE         b/se       b/se         -0.012       0.001         (0.069)       (0.068)         Yes       Yes         Yes       Yes	FE         FE         IV-FE           b/se         b/se         b/se           -0.012         0.001         (0.068)           (0.069)         (0.068)         -0.015           (0.089)         -0.010         (0.089)           Yes         Yes         Yes           Yes         Yes         Yes

Note: \*\*\* stands for significant at the 0.01 level, \*\* at the 0.05 level and \* at the 0.1 level. Robust SE in parenthesis.

Table 5: Estimations of the Impact of Migration on Wages of Migrant Workers (Group ID: education-experience)

	(1)	(2)	(3)	(4)
	$\mathbf{FE}$	$\mathbf{FE}$	IV-FE	IV-FE
	b/se	b/se	b/se	b/se
Proportion of Migrant workers	-0.180	-0.205		
	(0.164)	(0.201)		
Proportion of High skill migrants			-0.565	-0.145
			(0.459)	(0.629)
Proportion of Low skill migrants			-0.049	-0.227
			(0.143)	(0.186)
Quarter FE	Yes	Yes	Yes	Yes
Education <sup>*</sup> Year FE	Yes	Yes	Yes	Yes
Experience*Year FE	Yes	Yes	Yes	Yes
Observations	1446	1357	1446	1357
R-squared	0.150	0.0661	0.150	0.0661

It could be the case that migration flows affect workers differently depending on their educational level. To address this issue, we re-estimated the model with a set of interactions. We interact our migrant share with dummy variables of 'primary complete', 'secondary complete' and 'university complete'. We also address the endogeneity issue in this specification, by using instrumental variables generated as interactions of each educational dummy variable with the past settlement instrument used in the previous section. The second stage results, shown in tables A.3.1 and A.3.2, indicate that most of the effects are non-statistically significant, with two exceptions. On the one hand, we find a negative effect (significant at the 5% level) of migration on Costa Rican workers with secondary complete education in the IV-FD specification (Table A.3.1, column 4). On the other hand, we also find a negative effect (10% significance level) of migration on wages of migrant workers with primary complete education in the IV-FD specification (Table A.3.2). Finally, we analyze the heterogenous effect depending on the educational level using the "national labor market" approach. The results, in tables A.4.1 and A.4.2 in the Appendix, do not show any heterogenous effects of migration on wages of any workers.

The main insight of this section is that the result of non-significant effects of migration on wages of both Costa Ricans and migrants is robust to changes both in the estimation method and to changes in the composition of the groups ("national labor market" approach). Regarding the heterogenous effects by educational level of Costa Ricans and migrant workers, we observe some effects, but those are very specific and sensitive to changes in the specification and hence, are non-robust.

### 6 Conclusion

In this paper, we analyzed the effect of migration in Costa Rica on wages of both Costa Rican and already settled migrant workers. We exploit the variation within education-experience-region groups, which are built using quarterly labor force survey data from 2011 to 2019. The main estimation framework is based on panel data techniques and instrumental variables that allow us to control for unobserved heterogeneity and reverse causality, respectively.

The main results indicate that, on average, immigration has no effect on the wages of both natives and resident migrant workers with comparable skills. These results are robust to changes in the composition of the groups. Results are similar using education-experience groups instead of education-experience-region groups as the unit of the panel. The outcomes also hold when changing the panel data estimation strategy, that is, departing from the within transformation and estimating the main models with the variables in first differences. We also find that depending on education level, negative and significant effects are observed, in particular for high-skilled workers. Nevertheless, these outcomes are very specific and sensitive to changes in the model specification.

These outcomes suggest that over the period 2011-2019 the expected negative effect of migration on wages of workers with comparable skills has possibly been counteracted by some structural parameters of the production function and structural changes in the economy. The main factors dampening the effect of migration on wages could be: the potential complementarity between recently arrived migrants and domestic workers with comparable skills; the rational response of domestic workers by moving from manual tasks to communication intensive tasks; an increase in the demand of the now more abundant low-skilled workers induced by a change in the output mix of firms; and a change towards a technology that is intensive in low-skilled workers. Since the first explanation is more related to the elasticities of substitution of the production function, while the last three are more related to adjustment mechanisms, there are two possible explanations to rationalize the results. Either there is an important degree of complementarity between recently arrived migrants and domestic workers in Costa Rica, or the response of workers and firms in Costa Rica is fast. We leave these two issues for further research. A second topic for further investigation is the validation of any of the potential explanations given for the suggested counteracting effects.

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# A Appendix

#### A.1 Calculation of marginal effects

To interpret the final coefficient, we must convert it to an elasticity which represents the percent change in wages with respect to a percent change in labor supply originated by the migration flow. Lets define for example  $m_{ijrt} = \frac{M_{ijrt}}{C_{ijrt}}$  as the percentage increase in labor supply attributable to immigration. Then, the final effect of migration on the wage of native Costa Ricans is estimated as follows: We have that:

$$p_{ijrt} = \frac{M_{ijrt}}{M_{ijrt} + C_{ijrt}} = \frac{\frac{M_{ijrt}}{C_{ijrt}}}{\frac{M_{ijrt}}{C_{ijrt}} + 1} = \frac{1}{1 + \frac{C_{ijrt}}{M_{ijrt}}} = \frac{1}{1 + \frac{1}{m_{ijrt}}}$$
(9)

Then, according to the chain rule:

$$\frac{dlogy_{ijrt}}{dm_{ijrt}} = \frac{dlogy_{ijrt}}{dp_{ijrt}}\frac{dp_{ijrt}}{dm_{ijrt}} = \frac{\beta_1}{(1+m_{ijrt})^2}$$
(10)

Where  $\beta_1$  is the coefficient of our regression and  $m_{ijrt}$  is evaluated at the means.

#### A.2 First stage regressions

Table A.2.1: FE First Stage Estimations of the impact of Migration on wages of Costarican workers (Group ID: education-experience-region)

	(1)	(2)	(3)
	First stage	First stage	First stage
	Prop.Migrants	Prop.High Skill Migrants	Prop.Low Skill Migrants
Pastsettlement_Instrument	0.670***		
	(0.043)		
Pastsettlement_InsHighskill		$0.497^{***}$	-0.000
		(0.048)	(0.007)
Pastsettlement_InsLowskill		0.001	0.772***
		(0.005)	(0.056)
Quarter FE	Yes	Yes	Yes
Education*Year FE	Yes	Yes	Yes
Experience <sup>*</sup> Year FE	Yes	Yes	Yes
Region <sup>*</sup> Year FE	Yes	Yes	Yes
Observations	9042	9042	9042
F-test Robust	11.86	21.00	62.68
R-squared	0.151	0.111	0.174

	(1)	(2)	(3)
	First stage	First stage	First stage
	Prop.Migrants	Prop.High Skill Migrants	Prop.Low Skill Migrants
Pastsettlement_Instrument	0.670***		
	(0.043)		
Pastsettlement_InsHighskill		$0.497^{***}$	-0.000
		(0.048)	(0.007)
Pastsettlement_InsLowskill		0.001	0.772***
		(0.005)	(0.056)
Quarter FE	Yes	Yes	Yes
Education*Year FE	Yes	Yes	Yes
Experience <sup>*</sup> Year FE	Yes	Yes	Yes
Region <sup>*</sup> Year FE	Yes	Yes	Yes
Observations	9042	9042	9042
F-test Robust	11.86	21.00	62.68
R-squared	0.151	0.111	0.174

Table A.2.2: FE First Stage Estimations of the impact of Migration on wages of Migrant workers (Group ID: education-experience-region)

Note: \*\*\* stands for significant at the 0.01 level, \*\* at the 0.05 level and \* at the 0.1 level. Robust SE in parenthesis.

#### A.3 Heterogenous effects by educational level (spatial correlation approach)

Table A.3.1: Fixed Effects and Instrumental Variable-Fixed Effect Estimations of the impact of Migration on wages of Costa Rican workers (Group ID: education-experience-region)

	(1)	(2)	(3)	(4)
	$\mathbf{FE}$	FD	IV-FE	IV-FD
	b/se	b/se	b/se	b/se
Effect by educational level				
Primary complete	0.020	0.013	0.090	-0.010
	(0.041)	(0.052)	(0.088)	(0.073)
Secondary complete	-0.034	-0.018	0.063	-0.170**
	(0.042)	(0.052)	(0.084)	(0.083)
University complete	0.035	0.007	0.176	0.046
	(0.071)	(0.085)	(0.291)	(0.254)
Quarter FE	Yes	Yes	No	No
Education <sup>*</sup> Year FE	Yes	Yes	No	No
Experience <sup>*</sup> Year FE	Yes	Yes	No	No
Region <sup>*</sup> Year FE	Yes	Yes	No	No
Observations	9063	8626	8957	8550
R-squared	0.132	0.0166	0.132	0.920

	(1)	(2)	(3)	(4)
	$\mathbf{FE}$	FD	IV-FE	IV-FD
	b/se	b/se	b/se	b/se
Effect by educational level				
Primary complete	-0.116	-0.223**	0.046	-0.237*
	(0.072)	(0.089)	(0.140)	(0.122)
Secondary complete	-0.141	-0.208	-0.004	0.382
	(0.121)	(0.143)	(0.317)	(0.267)
University complete	-0.480	-0.438	-1.410	-2.253
	(0.334)	(0.484)	(2.074)	(1.583)
Quarter FE	Yes	Yes	No	No
Education <sup>*</sup> Year FE	Yes	Yes	No	No
Experience <sup>*</sup> Year FE	Yes	Yes	No	No
Region <sup>*</sup> Year FE	Yes	Yes	No	No
Observations	5718	4531	4361	3707
R-squared	0.0467	0.0293	0.0612	0.579

Table A.3.2: Fixed Effects and Instrumental Variable-Fixed Effect Estimations of the impact of Migration on wages of Migrant workers (Group ID: education-experience-region)

Note: \*\*\* stands for significant at the 0.01 level, \*\* at the 0.05 level and \* at the 0.1 level. Robust SE in parenthesis.

## A.4 Heterogenous effects by educational level (national labor market approach)

Table A.4.1: Fixed Effects and Instrumental Variable-Fixed Effect Estimations of the impact of Migration on wages of Costarican workers (Group ID: education-experience)

	(1)	(2)	
	$\widetilde{\mathrm{FE}}$	$\overline{\mathrm{FD}}$	
	b/se	b/se	
Effect by educational lev	vel		
Primary complete	-0.173	-0.298	
	(0.147)	(0.199)	
Secondary complete	0.058	0.223	
	(0.303)	(0.343)	
University complete	-0.885	-0.738	
	(1.025)	(1.218)	
Quarter FE	Yes	Yes	
Education*Year FE	Yes	Yes	
Experience*Year FE	Yes	Yes	
Observations	1446	1357	
R-squared	0.151	0.0671	

Table A.4.2: Fixed Effects and Instrumental Variable-Fixed Effect Estimations of the impact of Migration on wages of Migrant workers (Group ID: Skill)