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Heterogeneous Labor Impacts of Migration Across Skill Groups: The Case of Costa Rica*

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Abstract

Popular empirical strategies that examine the labor impacts of migrants, like the skill-cell approach, are frequently used to measure the effects of immigrants from a particular skill group on native-born workers with similar skills. I use an augmented version of the skill-cell approach to examine the impacts of immigrants on native workers with similar skills but also across skill groups. I apply this approach to the case of Nicaraguan immigrants in Costa Rica. I find large positive employment and wage effects on high-skilled women arising from low-skilled migrants. These positive effects are derived from both the household channel and the complementary-skills channel. I also find negative but small effects on low-skilled native workers. The results show that immigrants can have complex labor market effects on native workers with own and cross elasticities that can be quite different.

Keywords: International migration, skill-cell, employment

JEL Classification: J60, J61, F22

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1 Introduction

The effect of immigration on native's labor market outcomes depends on how substitutable or complementary immigrants and natives are in the labor market. Immigrants are substitutes for native-born workers when they compete for similar jobs which can cause displacement and/or lower wages. Immigrants are complements when they increase the demand for complementary production tasks and skills of the native workers. Popular empirical strategies that examine the labor impacts of migrants, like the skill-cell approach, are frequently used to measure the effects of immigrants on native-born workers with similar skills. But the same immigration shock can both cause substitutability and complementarity in the labor market depending on the skill of the native worker. Consider, for example, low-skilled immigrants working as fruit pickers in the strawberry industry. The immigrants might be willing to supply their labor at lower wages than natives thus lowering the natives' salaries but also the strawberry grower's production costs. The growers might then increase output which may require hiring more high-skilled managers to supervise the expansion of production. In this example, the same group of migrants harmed low-skilled native workers by reducing their salaries but benefited high-skilled native individuals by increasing their employability.

In this paper I use a skill-cell approach to disentangle this type of differentiated impacts. The traditional skill-cell approach pioneered by Borjas (2003) divides the labor market into skill groups, and the change in immigrant inflows to skill groups is compared with the change in wages within those skill groups. I employ an augmented version of the skill-cell approach to examine the labor market effects that immigrants exert on native workers with similar skills but also across skill levels.[1]

The analysis is focused on to the case of Nicaraguan migration to Costa Rica; therefore, the study also contributes to expand the literature on South-South migration. Studies that evaluate the impact of migration across developing countries are rare in comparison to analyses that examine migration flows across developed countries or from developing to developed countries. The lack of studies looking at migration flows between developing countries leaves a vacuum in the migration literature because migrants from developing countries arriving to other developing countries might not necessarily have the same labor market effects as migrants arriving to developed countries which typically exhibit deeper labor markets, more mature industries and more resilient institutions. Therefore, this study contributes to a growing number of papers that provide evidence on the impact of South-South migration flows (Hatton and Williamson, 2005; Biavaschi et al., 2018; Gindling, 2009).

Two recent studies examine the Nicaraguan migration in Costa Rica in terms of the labor market (Gindling, 2009; Mora and Guzmán, 2019). This study is mostly related to Gindling (2009) who examines the impact of Nicaraguan immigrants on the earnings of Costa Rican workers. The analysis in Gindling (2009) relies on the pure skill-cell approach and thus it assesses whether immigrants are substitutes or complements to the native population within the same skill level but not across skill levels. As mentioned before, I adopt a novel empirical strategy that allows me to explicitly explore the impact of migrants on natives across skill-cells. As it will be shown below, this is a large effect in the case of Costa Rica and is generally a type of impact that is overlooked

[1] Borjas (2003) uses a structural approach to measure the wage effects of immigrants on natives with different skills. In this analysis I do not need to rely on a structural model

in the empirical analyses that rely on the skill-cell approach. Another difference from Gindling (2009) is that I evaluate the impact of immigration not only on earnings but also on employment. Looking at the employment rate is important because the labor market effects of migration can be absorbed not only through wage changes but also through employment changes. In fact, as the labor supply elasticity increases, the wage effects of migration tend to become more muted while the employment effects become larger (Dustmann et al., 2016). Thus, by looking at the response of earnings only, one might fail to detect important labor market adjustments from migration.

I find large positive employment and earnings effects on high-skilled women arising from low-skilled migrants. For example, a 1 percentage point increase in the share of low-skilled Nicaraguan workers raises the likelihood of being employed by about 4.5 percentage points for high-skilled women. These positive effects are derived from both the household channel and the complementary-skills channel. I also find negative but small employment impacts on low-skilled native workers arising from similar skill levels. In general, the findings indicate that migrants can have complex labor market effects on native workers with own and cross elasticities that can be quite different.

The rest of the paper is organized as follows. Section 2 discusses the immigration flows between Nicaragua and Costa Rica. Sections 3 presents the empirical strategy. Section 4 describes the datasets employed. Section 5 discuss the results and section 6 provides concluding remarks.

2 Nicaraguan migration to Costa Rica

Nicaraguans have migrated to Costa Rica for years; nevertheless, the share of Nicaraguan immigrants in the total population of Costa Rica was still below 2% by the early 1980s. Significant increases in migration took place starting from this period. With the outbreak of the armed conflict between the Sandinista government and the Contra forces in 1984 a period of migration predominantly for political reasons took place until the end of Nicaragua's civil war in 1990 (Otterstrom, 2008). After this period marked by military conflict, the causes for migration turned more economic in nature, particularly after Nicaragua implemented drastic structural adjustment policies between 1993 and 1997 (IOM, 2001). Catastrophic flooding from the slow motion of hurricane Mitch in 1998 also triggered an additional wave of immigration during this time. Accordingly, the share of Nicaraguan immigrants in the total population of Costa Rica increased sharply from 1.95% in 1984 to 5.9% in 2000. Nicaraguan migrants continued to be attracted to Costa Rica after 2000 given the country's political stability and much higher living standards than Nicaragua's. The share of Nicaraguans in Costa Rica's total population increased to 6.13% by 2010 and to 7.01% by 2018.[2] Most notably, the share of migrants from Nicaragua in the working-age population increased even more during this period, from 7.82% in 2010 to 9.05% in 2018 (see Figure 1).[3] In this study I focus on this 2010-2018 period and examine the potential labor market impacts from this rise in predominantly economic migrants. I also concentrate the analysis to this period because this allows me to address potential endogeneity concerns that I discuss in section 3 below.

To get a sense of the Nicaraguan immigrants in Costa Rica, table 1 (upper panel) shows some basic demographic characteristics of this population based on Costa Rica's household survey. The most notable characteristic is that a large percentage of these immigrants are low skilled. In 2018,

[2] Nicaraguans represent around 75% of the stock of all immigrants in Costa Rica

[3] The data source of Figure 1 is the Costa Rican household survey, ENAHO

for example, 78.6% of the working-age migrants had secondary education incomplete or less, and only 2% had completed tertiary education. This contrasts with the working-age native population in which 58.3% show an incomplete secondary education or less, while 9% possess a tertiary education degree (see lower panel of table 1).

Given the low levels of education, Nicaraguans tend to work relatively more than Costa Ricans in low skilled jobs. Table 2 shows, for example, that 50% of Nicaraguans are employed in elementary occupations.[4] The corresponding figure for Costa Ricans is 22%. Conversely, while 27% of Costa Rican workers are employed as managers, professionals or technicians only 6% of the Nicaraguans hold this type of jobs.

The evidence in these tables indicates that because of the relatively low levels of education relative to the Costa Rican population, the majority of the Nicaraguan immigrants tend to be absorbed in low-skilled jobs. The main questions that this paper seeks to address are: how the employment of Nicaraguans in low-skilled jobs affects the native population with similar low skills and whether this low-skilled migration has additional impacts on higher skills Costa Ricans.

3 Empirical methodology

To measure the impact of migrants on the labor market I exploit variation of immigrant shares across geographic space and skill-cells (education and experience). This is called the mixture approach (Card, 2001; Dustmann et al., 2016) which combines the pure spatial approach led by Altonji and Card (1991) with the skill-cell approach pioneered by Borjas (2003). The mixture approach has been used recently by Llull (2018), Borjas (2006), Card and Peri (2016), Biavaschi et al. (2018). The baseline empirical specification of the typical mixture approach relies on the following functional form:

$$Y_{ijrt} = \alpha_0 + \beta \cdot m_{jrt} + \bar{X}_{ijrt} \cdot \gamma + \alpha_j + \alpha_r + \alpha_t + (\alpha_j \cdot \alpha_r) + (\alpha_j \cdot \alpha_t) + (\alpha_r \cdot \alpha_t) + e_{ijrt} \quad (1)$$

with:

$$m_{jrt} = \frac{M_{jrt}}{M_{jrt} + N_{jrt}} \quad (2)$$

where Y_{ijrt} is the labor outcome of interest for a native individual i in skill group j in region r at time t; M_{jrt} is the number of Nicaraguan workers in skill group j in region r at time t; N_{jrt} is the corresponding number of natives; $\bar{X}_{ijrt}$ is a vector of individual characteristics, including gender and marital status; α_j, α_r, and α_t are skill-cell, region and year fixed effects, respectively, and e_{ijrt} is the error term, which are clustered at the skill-region-year level. Our paramenter of interest is β. Borjas (2003) defines this parameter the 'own elasticity' of substitution/complementarity because it measures the labor market impact of a migrant on a native that exhibits the same skills. Below, I introduce additional terms to equation (1) to measure also the impact of a migrant on a native that exhibits different skills (cross-elasticity).

The migration shares in (2) are defined at the skill-region-year level.[5] In order to provide

[4] Among the elementary occupations, many Nicaraguans work in activities of households as employers, like cleaners or nannies. The share of Nicaraguan workers in these occupations is 18%

[5] Throughout the paper all the shares are expressed in percent

some intuition behind this calculation, I start by describing the calculation of the migration shares by skill group at the national level, $m_{jt} = M_{jt}/(M_{jt} + N_{jt})$. First, I select the number of cells so that there is a high enough number of migrants in each cell. Since I am using a household survey to calculate these shares, having too many cells could lead to a too few observations of Nicaraguan migrants in the survey for some of the cells, particularly for the higher skill cells. This would make the calculation of the migrant shares in those cells noisy. Accordingly, I selected 10 cells that combine different levels of education and experience. In particular, the 10 cells consist of 5 education groups (primary incomplete, primary complete, secondary incomplete, secondary complete and tertiary complete) and two experience levels (below or equal and above 15 years). I calculate these migrant shares for each cell at the national level using the yearly household surveys. For comparison purposes, I also compute these same shares using the 2011 census and contrast them with those from the 2011 household survey. Table 3 shows that the shares from both data sources are very similar which give us confidence that the survey is doing an adequate job capturing the Nicaraguan migration.

Now I calculate the migrant shares in (2). For this, I need a measure for the number of migrant workers that varies by skill, region and year, M_{jrt}. I obtain M_{jrt} as follows:

$$M_{jrt} = \frac{M_{jr1984}}{M_{j1984}} \cdot M_{jt} \tag{3}$$

where M_{jr1984}/M_{j1984} is the share of Nicaraguan workers in skill group j in region r that I take from the 1984 census, and M_{jt} is the number of Nicaraguan workers of skill j at time t at the national level that I obtained from the household surveys.[6] In expression (3), Nicaraguan migrants of skill group j in year t are apportioned across geographic space according to the historical distribution of Nicaraguan immigrants in the year 1984. Note that this is the basis for the popular shift-share instrument which interacts national inflows of immigrants with the geographic distribution of the immigrants in the past. The instrument, introduced by Altonji and Card (1991) and further developed by Card (2001) is often employed to address the fact that the location of immigrants across regions is not random as there could be factors that affect the current location decision of immigrants across region that also affect current outcomes Y_{ijrt}. If this is the case, the estimates of the migration effects on the labor market could be biased. The instrument rely on the fact that migrants tend to locate in areas where there are already settlements of their co-nationals (Bartel, 1989); therefore, if the settlements formed in the past are uncorrelated with the current outcomes, distributing the migrants by such settlements can address the endogeneity problem.

There could be, however, local conditions in the past that could be persistent affecting the location of migrants. For instance, if places that have better employment opportunities attract more migrants and the correlation overtime is strong, this channel can bias the estimates. Therefore, following Mayda et al. (2018), I perform a falsification exercise by regressing the change in the subsequent share of migrants on past outcomes. In particular, I regress the change in the share of migrants at the region-skill level during the treatment period (2010-2018) on changes in two outcome variables (employment rate and average earnings) in a pre-treatment period (2000-2009). In both cases, the coefficients are actually negative but not statistically significant.[7]

[6] In principle I could have used the information from the household surveys which is representative at the regional level, but the calculation of the migrant shares for some of the skill-region-year cells could be potentially noisy because there are only a few observations of Nicaraguan migrants in some of these cells

[7] The estimated coefficients for the employment rate and for the average earnings are -0.143 and -0.008, respectively, with p-values of 0.46 and 0.85, respectively

Note that since I do not observe directly m_{jrt} in (1), I employ expression (3) to construct (2) which then enters (1). Accordingly, instead of estimating an instrumental variables specification, I estimate a reduce form equation in which (3) enters equation (1) though expression (2).[8]

One recent criticism to the validity of using early migrant networks to study the impacts of migrants in destination countries is that migration could be serially correlated in which past migration could cause both current outcomes and current migration (Jaeger et al., 2018). I mentioned above that I found no evidence of persistence between labor outcomes and the location of migrants. Moreover, to construct the predicted number of migrants in (3), I have chosen a distribution of Nicaraguan migrants that is sufficiently distant in the past, the year 1984. This year predates not only the recent flow of economically motivated migrants but also the migrants that left Nicaragua for politically motivated reasons due to the civil war between 1984 and 1990.[9]

The final specification exploits variation of immigrant shares across 10 skill groups, 6 regions and 9 years.[10] Finally, the outcome variable Y_{ijrt} in equation (1) is either a dummy variable equal to 1 if the individual is employed (and zero otherwise), or the log of hourly earnings of the worker.

4 Data description

The outcome variables and the vector of individual characteristics for the Costa Rican population are taken from the Household Survey (*ENAHO*). This is a repeated cross-section survey that is conducted annually by the *Instituto Nacional de Estadística y Censos*. I employ data from 2010 to 2018. I focus on individuals between 15 and 65 years of age and exclude the inactive population.

The household survey includes information regarding the country where the individual was born. We employ this information to identify the Nicaraguan immigrants in the dataset and to construct the migration shares, as explained above. Comparing the household survey with the last population census in Costa Rica of 2011, provides a sense of how well the ENAHO captures de Nicaraguan immigrants. For example, according to the population census, the share of Nicaraguans in Costa Rica in 2011 was equal to 6.79% while the share of Nicaraguans in Costa Rica in the same year was 6.71% according to the household survey. As mentioned above, a comparison of the migrant shares at the skill level between the 2011 census and ENAHO 2011 also indicate that the survey captures adequately the Nicaraguan migration (see table 3).

Finally, I use the Costa Rican population census of 1984 to construct M_{jr1984}/M_{j1984} in equation (3). Therefore, I employ information of the distribution of Nicaraguan migrants in Costa Rica that predates the start of the analysis by 26 years.

[8] To check that Nicaraguan immigrants tend to locate close to family and friends who came in the past, I compare the distribution shares of Nicaraguan migrants at the skill-region level between the 1984 and 2011 censuses. The correlation of these shares is 0.94, indicating that the location of Nicaraguan migrants highly depends on their networks originated in the past

[9] As noted by Blau and Kahn (2015), the finding by Blanchard and Katz (1992) that the wage effects of local employment shocks die out within 10 years provides support for employing intervals of 10 or more years between the previous immigrant settlement and the current inflows

[10] Costa Rica has 6 socio-economic regions: Central, Chorotega, Pacífico Central, Brunca, Huetar Atlántica and Huetar Norte

5 Estimation Results

Table 4 presents summary statistics of the main variables in equation (1) while table 5 shows the baseline results. Columns (1) to (3) from table 5 show the results for employment while columns (4) to (6) show the results when the dependent variable is the log of hourly wages. Nicaraguan immigrants impact negatively Costa Rican workers through employment with an effect that appears larger (in absolute values) for women than for men: a 1 percentage point increase in the share of migrants reduces the probability of being employed in 0.25-0.55 percentage points. This is not a very large effect. Note from table 4 that the probability of being employed is 0.91 (or 91 percent) and that the average migration share (same skill cell) went from 8.23% in 2010 to 9.72% in 2018. Therefore, the average increase in the migration shares during this period is associated with a reduction in the probability of being employed of about 0.37 percentage points for men and 0.82 percentage points for women.[11] No statistically significant impact was found with respect to earnings.

We can allow the own elasticity of substitution to differ for individuals below and above secondary education. Borjas (2003), for example, shows that the own elasticity of substitution differs across educational groups. Table 6 shows the results, where 'low-skilled' refers to individuals with at most secondary education incomplete, while 'high-skilled' refers to individuals with secondary education completed or more (see table 3). Interestingly, only low-skilled individuals are negatively impacted by migrants, as shown by columns (1) and (2), albeit the impacts are still small. The employment impacts on high-skilled Costa Ricans are not statistically significant, as indicated by columns (3) and (4). Once again, we found no sigificant effects in terms of wages. The results in table 6 go in line with those in Borjas (2003) indicating that the own elasticity of substitution can differ across educational groups.

As mentioned before, one limitation with equation (1) is that the specification compares the relationship between immigrants and natives within the same skill cell and thus it only identifies the impact that migrants of skill j have on native workers within the same skill (own elasticity). In principle, the impact of Nicaraguan migrants on the native population could extend beyond similar skill groups. As shown in section 2, Nicaraguan migrants in Costa Rica are predominantly low skill (see table 1) and thus their insertion in the labor market is more concentrated in elementary occupations (see table 2). It is then reasonable to expect that Nicaraguan workers could negatively affect Costa Rican workers with the same low skills when they compete for similar jobs, but they could also impact native individuals with higher skills in a number of ways. For instance, the presence of low-skilled immigration might reduce the costs of production in certain sectors, raising their output and thus the demand for higher-skilled natives. This is a complementary-skills channel. Low-skilled immigrants could also lower the costs of household services allowing high-skilled individuals that stay at home to increase their supply of labor (Cortés and Tessada, 2011). This is a household channel. Note that none of these effects can be captured by equation (1).

To measure the potential impacts of Nicaraguan migration on Costa Ricans across skill levels (cross elasticities), I augmented specification (1) incorporating two additional terms, m_{j^-rt} and m_{j^+rt}, as follows:

$$Y_{ijrt} = \alpha_0 + \beta_0 \cdot m_{jrt} + \beta_1 \cdot m_{j^-rt} + \beta_2 \cdot m_{j^+rt} + \bar{X}_{ijrt} \cdot \gamma + \alpha_j + \alpha_r + \alpha_t + ... + e_{ijrt} \quad (4)$$

[11] For men, this is calculated as follows: $(9.72 - 8.23)x(-0.0025)x100 = 0.37$. For women: $(9.72 - 8.23)x(-0.0055)x100 = 0.82$

with:

$$m_{j^-rt} = \frac{\sum M_{j^-rt}}{\sum M_{j^-rt} + \sum N_{j^-rt}} \tag{5}$$

$$m_{j^+rt} = \frac{\sum M_{j^+rt}}{\sum M_{j^+rt} + \sum N_{j^+rt}} \tag{6}$$

where M_{j^-rt} is the sum of all the Nicaraguan workers that belong to a skill level below j and N_{j^-rt} is the corresponding number of natives. Similarly, M_{j^+rt} is the sum of all the Nicaraguan workers that belong to a skill level above j and N_{j^+rt} is the corresponding number of natives. I rank the skill levels of individuals according to their education and experience as they appear in table 4. For example, for an individual with secondary education incomplete and 15 years or less of experience, the lower skill group is the sum of the following migrants: primary complete and more than 15 years, primary complete and less than 15 years, primary incomplete and more than 15 years and primary incomplete and less than 15 years. Similarly, the higher skill group to this skill level is the sum of the following individuals: secondary incomplete and more than 15 years, secondary complete and less than 15 years, secondary complete and more than 15 years, tertiary complete and less than 15 years and tertiary complete and more than 15 years.[12] For an individual in a skill level j, β_0 measures the labor market effects from the share of immigrants with similar skills (own elasticity), while, β_1 and β_2 measure the effects from the share of immigrants with lower skills and higher skills, respectively (cross elasticities).

Table 7 presents the results of estimating equation (4). The structure of the table is similar to the one in table 6 but with the additional terms for the cross elasticities. Before commenting the results, it is worth mentioning that one econometric concern with this equation is the possibility of multicollinearity among the migration terms. Multicollinearity, however, is not an issue in this case. I calculate variance-inflation factors (VIF) after running each regression and they show values below the critical threshold of 5, indicating no presence of multicollinearity.[13] Another indication of no multicollinearity is that the estimated values for the first migration term (with same skills) do not significantly vary from those in table 6 when we introduce the other migration shares.

Compared to table 6, an important new result arises with respect to high-skilled women. In particular, column (4) shows that high-skilled women exhibit a positive impact from Nicaraguan migrants of lower skills: a 1 percentage point increase in the share of migrants of lower skills increase the probability of being employed by about 4.5 percentage points. This is a large effect. Note that the average migration share (lower skill cells) increased from 15.77% in 2010 to 18.47% in 2018 (see table 4). Therefore, the average increase in this migration share during this period is associated with an increase in the likelihood of being employed by about 15.9 percentage points.[14] Similarly, high-skilled women also experience a positive impact through earnings: a 1 percentage point increase in the share of migrants of lower skills increase hourly earnings of high-skilled women by about about 7.2%.

While the results from table 7 are revealing, it is important to explore further what are the channels through which high-skilled women benefit from lower skill migrants. First, it would be

[12] Note that (5) and (6) take the value of zero for individuals with skill-cells in the tails (primary incomplete with 15 or less, and tertiary complete with 15 or more), as there are no immigrants below or above these tails

[13] The VIF values for regressions in columns (1), (2), (3), (4), (5), (6), (7) and (8) of table 7 are 3.36, 3.45, 4.10, 4.01, 3.39, 3.51, 4.04 and 3.90, respectively

[14] This is calculated as follows: $(18.47 - 15.77)x(0.0448)x100 = 12.09$

insightful to examine whether the positive impacts arise from migrants with lower skills withing the same high-skilled educational group as the native women or from migrants in the low-skilled group. So far, we know that a high-skilled woman (for instance, a woman with tertiary education complete) benefits from migrants with lower skills, but we do not know if she benefits from migrants with lower skills within the same high-skilled educational group (for instance, a migrant with secondary education complete) or from migrants with lower skills in the low-skilled educational group (for instance, a migrant with secondary education incomplete).

I address this issue by introducing a new term in equation (4), $m^{hs}_{j^-rt}$. This is the share of migrants that belong to a skill level below j but within the same high-skilled educational group as the native-born individual. For example, for a native with tertiary education complete and 15 years or less of experience, the lower skill migrants *within* the same high-skilled educational group is the sum of the following migrants: secondary complete and more than 15 years of experience, and secondary complete and less than 15 years. Note that I cannot construct an equivalent measure for the migrants with lower skills in the low-skilled educational group because there is not sufficient variation to estimate this coefficient. This is because for any skill cell in the high-skilled group, the sum of migrants with lower skills in the low-skilled educational group is always the same. Therefore, I include $m^{hs}_{j^-rt}$ but also leave m_{j^-rt} in equation (4). Since now $m^{hs}_{j^-rt}$ is controlling for the impact of migrants with lower skills within the same high-skilled educational group, the coefficient estimate for m_{j^-rt} will capture the impact of migrants with lower skills from the low-skilled educational group.

For completeness, I also include the term $m^{ls}_{j^+rt}$ when I run the regressions for the low-skilled individuals. This is the share of migrants that belong to a skill level above j but within the same low-skilled educational group as the native-born individual. Same as before, I include $m^{ls}_{j^+rt}$ and leave m_{j^+rt} in equation (4). For the regressions focused on low-skilled individuals, $m^{hs}_{j^-rt}$ now controls for the impact of migrants with higher skills within the same low-skilled educational group; therefore, the coefficient estimate for m_{j^+rt} will capture the impact of migrants with higher skills from the high-skilled educational group.

Table 8 presents the results. Column (4) shows that the coefficient for the lower skill cell continues to be positive and significant with a similar value as in table 7. The same is true in column (8). Note also that the coefficient estimates for the lower skill cell within the high-skilled educational group are not statistically significant in neither column (4) nor column (8). These results imply that the positive effects on high-skilled women that we observed in table 7 are derived from low-skilled migrants and not from migrants with lower skills within the same high-skilled educational group. Column (7) also reveals that the earnings of high-skilled men seems to be negatively affected by migrants that possess lower skills than the natives but within the same high-skilled educational group.

The results in table 8 indicate that high-skilled women in Costa Rica are benefiting from low-skilled migrants, but there could be alternative channels by which these effects are taking place. For instance, Cortés and Tessada (2011) find that low-skill immigration in the US increases the work hours of women in the top quartile of the wage distribution, which they attribute to the fact that low-skill immigration allowed these professional women to devote less time to household chores. This is a household channel. Alternatively, production costs in sectors that use as inputs more immigrant-intensive services might fall which could free resources for hiring more (high-skilled) native workers or paying them higher salaries. A relatively similar channel is presented in Peri and

Sparber (2009) who shows that producing goods and services requires firms to combine different types of tasks ranging from routine and manual to more complex and cognitive tasks, thus the increased supply of simple tasks from the inflow of immigrants may increase the demand for the more complex tasks to be provided by natives. This is a complementary-skills channel. To discern which channel is playing a role behind the postive impacts on high-skilled women, we run separate regressions for high-skilled women without dependents and with dependents. We define a woman as having dependents if she lives in a household with at least one relative who is 6 years old or younger or a relative over 65 years of age. The impact of immigration on individuals with family dependents has been analyzed before in Farré et al. (2011) and Hiller and Chatruc (2020). Note that if the positive impact is observed only on high-skilled women with dependents, the results will suggest that the household channel is an important one. Likewise, if the positive impact is observed only on women without dependents, the results will point at the complementary-skills channel as the main one.

Table 9 presents the results. The coefficients for the lower skills cells are all positive and significant in the four columns, indicating that both channels play a role in the positive effects that high-skilled women experience from low-skilled migrants, in both employability and earnings.[15] Separating high-skilled women with dependents from those without dependents also reveal a new result: in addition to the positive impact from low-skilled migrants, high-skilled women with dependents exhibit a negative impact in terms of employability from migrants with the same skills and from migrants with lower skills within the same high-skilled educational group (see column 2). These results are informative because it shows that not all high-skilled women are insusceptible of experience a negative impact from the migrant population, as previously implied by tables 6, 7 and 8. The new results show that high-skilled women with dependents can get an employment boost from low-skilled migrants -most likely from the household channel- but at the same time they face employment vulnerability from migrants with relatively similar skills.

Overall, the results in this paper show that migrants can have quite complex labor market effects by impacting native-born workers differently depending on their skill levels, their gender and their family responsabilities.

6 Concluding remarks

When countries receive a migration shock, the same group of immigrants could both cause substitutability and complementarity in the labor market depending on the skills of the native workers. While low-skilled immigrants can compete with native workers for similar jobs causing displacement, they can also complement native workers of different skills. But popular empirical strategies that examine the labor impacts of migrants, like the skill-cell approach, are frequently used to measure the effects of migrants on native-born workers with similar skills only.

I employ an augmented version of the skill-cell approach to examine the labor market impacts of immigrants on native workers with similar skills but also across skill levels. I apply this strategy to the case of the Nicaraguan migration to Costa Rica.

[15] Gindling (2009) shows a positive effect of migration on high-skilled women's earnings, a finding that the author argues might arise from the household channel. The results in Table 9 explicitly indicate that this is indeed one of the channels

I find that there are indeed heterogeneous impacts with own negative elasticities for low-skilled men and women and cross positive elasticities for high-skilled women. The latter is observed on high-skilled women with and without dependents which indicate that a combination of household and complementary-skills channels are driving the results. The findings also show that the employment of high-skilled women with dependents are much more vulnerable to migrants with relatively similar skills than the employment of high-skilled women without dependents, a result that reveals another layer of heterogeneity regarding the labor market impacts of migration.

The analysis in this paper indicate that immigrants can have quite complex labor market effects on native workers with own and cross elasticities that can be very different. The findings show that the effects can vary by skill level, gender and family responsabilities of the native-born. The results support other findings in the literature regarding the labor market impacts of immigrants on native individuals across skill levels. The study also contributes to a small but growing number of analyses that provide evidence regarding the impact of migration flows that occur between developing countries.

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Figure 1: Immigrants from Nicaragua

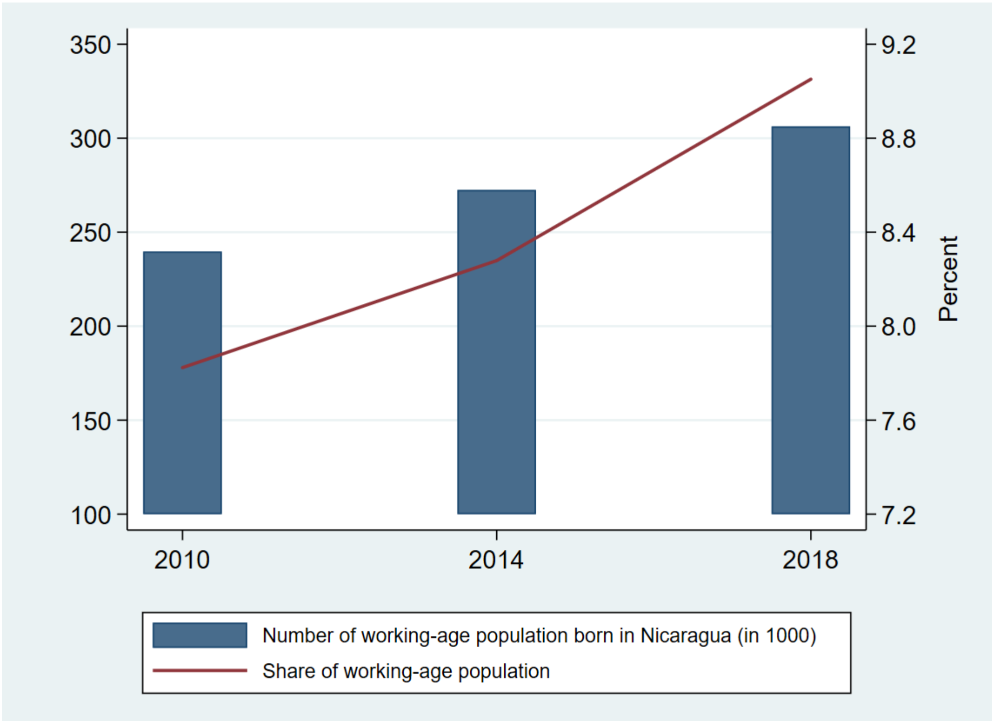

Table 1: Descriptive statistics of individuals aged 15-65 (percent)

Nicaraguans	**2010**	**2014**	**2018**
Age	33.9	36.0	37.5
Female (%)	54.3	54.7	54.2
Secondary incomplete or less (%)	84.2	78.8	78.6
Secondary complete (%)	14.9	19.1	19.3
Tertiary complete or more (%)	0.9	2.1	2.2
Costa Ricans	**2010**	**2014**	**2018**
Age	35.6	36.8	37.6
Female (%)	51.3	51.1	51.6
Secondary incomplete or less (%)	64.2	58.9	58.3
Secondary complete (%)	28.6	33.8	32.6
Tertiary complete or more (%)	7.2	7.3	9.1

Table 2: Distribution of employed individuals by occupation, 2018 (percent)

Occupation (ISCO-08)	**Costa Ricans**	**Nicaraguans**
Managers	2.0	0.4
Professionals	13.9	1.9
Technicians and Associate Professionals	10.7	3.4
Clerical Support Workers	9.0	2.5
Services and Sales Workers	21.6	21.8
Skilled Agr., Forestry and Fishery Workers	3.4	3.6
Craft and Related Trades Workers	10.2	12.7
Plant and Machine Operators and Assemblers	7.6	3.5
Elementary Occupations	21.6	50.0
Not specified	0.1	0.3

Table 3: Migration shares by education and experience (percent)

Education	Experience	Survey 2011	Census 2011
Primary incomplete	**years $\leq$ 15**	34	33
	years $>$ 15	23	25
Primary complete	**years $\leq$ 15**	14	13
	years $>$ 15	7	9
Secondary incomplete	**years $\leq$ 15**	13	12
	years $>$ 15	13	12
Secondary complete	**years $\leq$ 15**	7	7
	years $>$ 15	6	7
Tertiary complete	**years $\leq$ 15**	2	2
	years $>$ 15	3	3

Table 4: Summary statistics, main variables

	2010	**2014**	**2018**
Employment: Mean	0.92	0.91	0.91
Employment: Std. dev	0.27	0.29	0.28
Log of real earnings: Mean	6.02	6.11	6.19
Log of real earnings: Std. dev	0.79	0.83	0.78
Migration shares:			
Same skill cell: Mean	8.23	8.80	9.72
Same skill cell: Std. dev	7.47	7.46	7.56
Lower skill cells: Mean	15.77	16.63	18.47
Lower skill cells: Std. dev	12.22	11.34	12.95
Higher skill cells: Mean	4.13	4.66	4.80
Higher skill cells: Std. dev	2.60	2.58	2.59
Lower skill cells within high-skilled category: Mean	15.77	16.63	18.47
Lower skill cells within high-skilled category: Std. dev	12.22	11.34	12.95
Higher skill cells within low-skilled category: Mean	4.13	4.66	4.80
Higher skill cells within low-skilled category: Std. dev	2.60	2.58	2.59

Table 5: Baseline results

Migration share:	Employment All (1)	Employment Men (2)	Employment Women (3)	Earnings All (4)	Earnings Men (5)	Earnings Women (6)
Same skill cell	-0.0035***	-0.0025***	-0.0055***	-0.0012	0.0006	-0.0023
	(0.0009)	(0.0009)	(0.0019)	(0.0022)	(0.0026)	(0.0050)
R-squared	0.0418	0.0322	0.0536	0.3217	0.3072	0.3483
Observations	133,054	82,417	50,637	111,125	69,410	41,715

Notes: The dependent variable in (1)-(3) is a dummy equal to 1 if the individual is employed and 0 if unemployed. The dependent variable in (4)-(6) is the log of real hourly earnings of the employed individuals. The main explanatory variable is the share of Nicaraguan workers in the labor force. Additional controls include gender and marital status and fixed effects for skill (education and experience), year, region and any two-way interaction FE. Robust standard errors adjusted for clustering at the skill-region-year level are in parentheses
*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 6: Migration impacts differentiated by educational groups

	Employment				**Earnings**			
	Low-skilled		**High-skilled**		**Low-skilled**		**High-skilled**	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
Migration share:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Same skill cell	-0.0028***	-0.0044**	0.0003	-0.0065	0.0028	-0.0048	-0.0133	-0.0187
	(0.0010)	(0.0021)	(0.0031)	(0.0051)	(0.0026)	(0.0059)	(0.0154)	(0.0153)
R-squared	0.0323	0.0538	0.0301	0.0506	0.0581	0.0312	0.2462	0.2581
Observations	53,921	24,717	28,496	25,920	43,807	19,304	25,603	22,411

Notes: The dependent variable in (1)-(4) is a dummy equal to 1 if the individual is employed and 0 if unemployed. The dependent variable in (5)-(8) is the log of real hourly earnings of the employed individuals. The main explanatory variable is the share of Nicaraguan workers in the labor force in the same skill-cell as the individual in the dependent variable. Additional controls include gender and marital status and fixed effects for skill (education and experience), year, region and any two-way interaction FE. Robust standard errors adjusted for clustering at the skill-region-year level are in parentheses
*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 7: Migration impacts from similar and across skills

	Employment				**Earnings**			
	Low-skilled		**High-skilled**		**Low-skilled**		**High-skilled**	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
Migration shares:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Same skill cell	-0.0028***	-0.0044**	0.0002	-0.0022	0.0028	-0.0051	-0.0095	-0.0084
	(0.0010)	(0.0021)	(0.0031)	(0.0046)	(0.0027)	(0.0059)	(0.0156)	(0.0152)
Lower skill cells	-0.0010	0.0006	0.0077	0.0448***	0.0003	-0.0011	0.0220	0.0715***
	(0.0008)	(0.0012)	(0.0061)	(0.0074)	(0.0015)	(0.0036)	(0.0248)	(0.0229)
Higher skill cells	0.0033	0.0017	-0.0044	0.0005	-0.0240	-0.0408	0.0103	0.0341
	(0.0065	(0.0129)	(0.0046)	(0.0058)	(0.0164)	(0.0321)	(0.0233)	(0.0252)
R-squared	0.0324	0.0538	0.0301	0.0510	0.0581	0.0313	0.2463	0.2582
Observations	53,921	24,717	28,496	25,920	43,807	19,304	25,603	22,411

Notes: The dependent variable in (1)-(4) is a dummy equal to 1 if the individual is employed and 0 if unemployed. The dependent variable in (5)-(8) is the log of real hourly earnings of the employed individuals. The main explanatory variables are the share of Nicaraguan workers in the labor force in the same skill-cell as the individual in the dependent variable (first row), in lower skill-cells (second row) and in higher skill-cells (third row). Additional controls include gender and marital status and fixed effects for skill (education and experience), year, region and any two-way interaction FE. Robust standard errors adjusted for clustering at the skill-region-year level are in parentheses

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 8: Migration impacts from similar and across skills, additional results

	Employment				Earnings			
	Low-skilled		High-skilled		Low-skilled		High-skilled	
	Men	Women	Men	Women	Men	Women	Men	Women
Migration shares:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same skill cell	-0.0028***	-0.0045**	-0.0004	-0.0066	0.0025	-0.0057	-0.0293	-0.0094
	(0.0010)	(0.0021)	(0.0034)	(0.0049)	(0.0027)	(0.0060)	(0.0179)	(0.0173)
Lower skill cells	-0.0010	0.0006	0.0077	0.0445***	0.0002	-0.0011	0.0205	0.0715***
	(0.0008)	(0.0012)	(0.0061)	(0.0075)	(0.0015)	(0.0036)	(0.0246)	(0.0229)
Higher skill cells	0.0053	0.0057	-0.0056	-0.0080	0.0135	0.0072	-0.0278	0.0341
	(0.0103)	(0.0177)	(0.0059)	(0.0084)	(0.0234)	(0.0430)	(0.0275)	(0.0250)
Lower skill cells	–	–	-0.0015	-0.0110	–	–	-0.0467**	-0.0027
in H-S group			(0.0044)	(0.0085)			(0.0205)	(0.0249)
Higher skill cells	-0.0012	-0.0020	–	–	-0.0205**	-0.0233	–	–
in L-S group	(0.0039)	(0.0059)			(0.0101)	(0.0150)		
R-squared	0.0324	0.0538	0.0301	0.0510	0.0582	0.0313	0.2463	0.2582
Observations	53,921	24,717	28,496	25,920	43,807	19,304	25,603	22,411

Notes: The dependent variable in (1)-(4) is a dummy equal to 1 if the individual is employed and 0 if unemployed. The dependent variable in (5)-(8) is the log of real hourly earnings of the employed individuals. The main explanatory variables are the share of Nicaraguan workers in the labor force in the same skill-cell as the individual in the dependent variable (first row), in lower skill-cells (second row), in higher skill-cells (third row), in lower skill-cells within the high-skilled group (fourth row), and in higher skill cells within the low-skilled group (fifth row). Additional controls include gender and marital status and fixed effects for skill (education and experience), year, region and any two-way interaction FE. Robust standard errors adjusted for clustering at the skill-region-year level are in parentheses

*** ; ** ; * significant at the 1%, 5% and 10% level respectively

Table 9: Migration impacts on high-skilled women

	Employment		**Earnings**	
	Without dependents	**With dependents**	**Without dependents**	**With dependents**
Migration shares:	**(1)**	**(2)**	**(3)**	**(4)**
Same skill cell	0.0013	-0.0200**	-0.0099	-0.0009
	(0.0071)	(0.0080)	(0.0217)	(0.0296)
Lower skill cells	0.0462***	0.0310***	0.0678**	0.0758**
	(0.0124)	(0.0111)	(0.0296)	(0.0350
Higher skill cells	-0.0145	-0.0013	0.0330	0.0714
	(0.0118)	(0.0134)	(0.0313)	(0.0456)
Lower skill cells in H-S group	-0.0053	-0.0219*	-0.0237	0.0504
	(0.0124)	(0.0111)	(0.0310)	(0.0438)
R-squared	0.0576	0.0499	0.2528	0.2765
Observations	16,793	9,127	14541	7870

Notes: The dependent variable in (1)-(2) is a dummy equal to 1 if the high-skilled woman is employed and 0 if unemployed. The dependent variable in (3)-(4) is the log of real hourly earnings of the high-skilled woman. The main explanatory variables are the share of Nicaraguan workers in the labor force in the same skill-cell as the individual in the dependent variable (first row), in lower skill-cells (second row), in higher skill-cells (third row), and in lower skill-cells within the high-skilled group (fourth row). Additional controls include gender and marital status and fixed effects for skill (education and experience), year, region and any two-way interaction FE. Robust standard errors adjusted for clustering at the skill-region-year level are in parentheses

*** ; ** ; * significant at the 1%, 5% and 10% level respectively