Immigrants and the Portuguese labor market: Threat or Advantage?

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Abstract

In this study, we investigate the impact of the share of the foreign labor force on the wage of native workers in Portugal between 2010 and 2019 using linked employer-employee data from Quadros de Pessoal. By leveraging job characteristics from the O*NET skill taxonomy, we create more homogeneous skill groups, enabling a precise analysis of immigration's impact on specific skill sets. The empirical analysis, focusing on occupation-experience groups, reveals a positive association between native wages and immigrant shares. In contrast, when groups are based on education-experience, the relationship appears negative. These contradictory findings suggest that the impact of immigration on native wages varies significantly depending on how labor markets are segmented. Furthermore, our analysis demonstrates a positive and statistically significant effect on native wages in high-skilled occupations, while native wages in low-skilled occupations are negatively affected due to increased competition. Our findings highlight the importance of considering occupation classification over simple education levels and suggest that diverse results in existing literature may be due to sample averaging.

JEL Classification: J24, J31, J61

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1. Introduction

Migration shapes the fabric of our interconnected world, transcending borders and sparking debates on immigrant integration that resonate deeply in societies worldwide. Beyond mere movement, migration embodies the aspirations, struggles, and dreams of millions seeking better opportunities, safety, and belonging. It serves as a testament to the human spirit's resilience and adaptability in the face of adversity, driving cultural exchange, innovation, and economic growth. Economic research, which has long focused on the labor market effects of immigration (for example, Foged and Peri (2016), and Dustmann et al. (2017), and studies such as studies conducted by Card (2001, 2005), Dustmann et al. (2005), and Aydemir and Borjas (2007), have suggested that the disadvantages of immigration seem to outweigh its advantages. However, the literature does not remain entirely silent regarding the positive effects of immigrants either, as illustrated by Ortega and Peri (2009), Ottaviano et al. (2018), Khanna and Lee (2018), Tabellini (2019) and Burchardi et al. (2020), for example, who have claimed in favor of a positive impact.

On the topic of immigrant earnings in particular, it is commonly observed that immigrants earn less than native-born individuals. Clarke et al. (2019), for example, underscore this finding in their examination of immigrant income dynamics across the United States, Canada, and Australia. They also find that certain immigrant groups exhibit improvements in their earnings over time. There have been a large number of empirical studies that investigate the wage difference between natives and non-natives. One major factor is that immigrants often earn lower wages because the education they obtained abroad and the work experience they gained in their home countries are often undervalued in the host country (Christl et al., 2020; Aldashev et al., 2012; Dell'Aringa et al., 2015). Furthermore, whether an individual's education was acquired in the host country or their home country also significantly contributes to the wage difference between immigrants and natives (Fortin et al., 2016; Warman et al., 2015).

The primary aim of this paper is to empirically explore how the presence of immigrant workers affects the wages of native workers in Portugal between 2010 and 2019. While previous studies have often centered on larger economies, Portugal provides an intriguing contrast, offering a relatively smaller labor market landscape. This microcosm of labor dynamics permits a meticulous dissection of the effects of immigration, spotlighting nuances that might otherwise be overshadowed in larger economies. In a relatively less developed country where economic challenges have been a historical reality, the difficulties encountered by the local population in obtaining stable employment remain a prevailing concern. Hence, examining the effects of immigrants on wages in Portugal assumes paramount importance, as it provides valuable insights into the challenges stemming from the merging of diverse labor forces within the country, offering a deeper understanding of how the presence of immigrants can influence the job prospects of local individuals.

In this context, Portugal's historical legacy of emigration spanning centuries has experienced a notable shift in recent times. From significant waves of emigration in the late 19th century to the mid-20th century, to the marked transformation in contemporary immigration driven by economic changes and Portugal's accession to the EU in 1986. This accession facilitated greater mobility among member states and led to increased immigration from other EU countries, and from countries outside the EU as well. This phenomenon has brought considerable new opportunities and challenges, shaping Portugal's labor market and society in significant ways.

In examining the influence of immigration on the labor market outcomes of native workers, two primary methodologies emerge, which for simplicity may be labelled as education-experience and occupation-experience based. Typically, research has predominantly focused on categorizing workers based on their levels of formal education, a method pioneered by Borjas (2003) that ultimately assumes complete interchangeability between immigrants and natives within the labor market. However, the education-experience approach is likely to overlook the degree of heterogeneity in college degrees and their role in creating wage inequality (Ingram and Neumann, 2006). Similarly, wage gaps between immigrants and natives, as highlighted by Bratsberg and Terrell (2002) and Bratsberg and Ragan (2002), lead to lower returns to education for immigrants who complete their education abroad. Another limitation arises from education downgrading, as discussed by Dustmann et al. (2016), Mattoo et al. (2008), and Neagu (2009), where immigrants may experience a reduction in the perceived value of their formal education upon arrival in the host country.

A more recent approach, as employed by Sharpe and Bollinger (2020), introduces an innovative technique that provides fresh insights into the impact of immigration on occupational skill sets. This approach, akin in principle to the education-experience group methodology, employs a different stratification method. It involves collecting job characteristics based on the O*NET skill taxonomy, which creates more homogeneous skill groups, facilitating a more precise analysis of the impact of immigration on specific skill sets within occupations. By utilizing the O*NET data, we can indeed construct occupation groups that are more homogeneous in terms of the overall skill level, irrespective of an individual's nationality or citizenship status.

Our analysis reveals a number of interesting results. Firstly, the correlation between years of experience and immigrant penetration in various skill groups indicates a decreasing pattern in the representation of non-native individuals as the number of years of experience increases. This phenomenon suggests increased competition between workers with limited labor market experience and immigrants.

Furthermore, the elasticity of substitution between labor inputs shows that natives and immigrants are complementary to each other. Moreover, whenever workers are stratified based on their educational attainments, the share of immigrants has a significantly negative impact on native wages, a result that is strikingly reversed if occupational stratification is used instead. In the latter, a 1% increase in the share of immigrants within an occupation-experience group leads on average to a 0.357% increase in native wages. This positive effect of immigration on native wages is interesting, offering further support in favor of the results obtained by Ottaviano and Peri (2006), Dustmann et al. (2008), and Barrett et al. (2011).

Stratifying labor markets by occupations addresses certain methodological limitations detected in earlier approaches. It is nevertheless crucial to consider the potential endogeneity issue arising from occupational choice, as selection can be influenced by endogenous factors. To tackle this concern, we incorporate a shift-share instrument similar to the approach used by Card (2001). This instrument helps mitigate endogeneity issues and the corresponding results are statistically positive and in line with the findings from the OLS estimation.

To ensure the robustness of the occupation stratification and understand why the results from the two approaches differ, we then use refined classifications—sextiles, deciles, and ventiles—based on the communicative-to-manual skill ratio, as outlined by Sharp and Bolinger (2020). This helps verify if the results hold under different conditions, providing a more comprehensive assessment of the reliability of the main estimation. The results remain robust across various definitions of occupation groups based on occupational skills.

Moreover, we construct competition quartiles to assess the impact of immigrants on natives in situations where they resemble, or not, each other, using in particular the education-experience approach. Our findings show that the impact of immigrants on the wages of natives who are least similar to immigrants is positive and strongly significant, while there is a negative impact associated with the presence of foreign-born individuals in intense competition quartiles, where natives closely resemble foreigners. There is therefore confirmation that immigrants do not adversely affect the wages of natives who are least similar to immigrants, as in Sharpe and Bollinger (2020), and Borjas (2003), who also claimed that the effect of immigrants sems to be above all concentrated among less educated natives.

The remaining sections of the paper are structured as follows: In section 2, a comprehensive review of existing literature regarding the influence of immigrants on native wages is presented. Section 3 provides a detailed description of our dataset. Section 4 introduces the econometric approach employed in the analysis, along with the robustness tests conducted to ensure the reliability of the findings. The findings from the regression analysis are elaborated upon in Section 5, and finally, in Section 6, we summarize the key findings and implications derived from the research.

2. Literature review

The impact of immigration on native wages has been extensively studied in the literature, reflecting the complexity of labor market dynamics. Various factors, such as skill levels, occupational specialization, and economic conditions, shape the outcomes of immigration. While theoretical perspectives differ on the exact nature of the impact, empirical studies have revealed heterogeneous effects across skill groups and occupations. Low-skilled native workers often face more significant negative effects, while highly skilled natives may experience benefits or remain relatively unaffected.

These findings echoed early theoretical results such as the Rybczynski theorem (1955), which analyzed the effects of capital investment, immigration, and emigration within the Heckscher-Ohlin (H-O) model. Over time, a vast and rapidly expanding empirical literature has investigated various labor market outcomes, including wages, employment, and labor force participation, shedding light on the nuanced interactions between immigrant and native workers. Despite the diversity of findings, the overarching theme remains the intricate relationship between immigration and native labor market outcomes, influenced by factors ranging from the composition of the immigrant workforce to the regulatory environment and broader economic context.

Studies investigating the negative impact of immigration on native wages, such as those conducted by Aydemir and Borjas (2007), Borjas (2003), and Borjas et al. (2008), highlight labor market competition between native workers and immigrants as a key factor. They suggest that an influx of immigrant labor can exert downward pressure on wages, especially in low-skilled occupations or industries where immigrants are concentrated. Immigrants, often willing to accept lower wages due to factors like different labor market experiences or institutional barriers, may displace native workers or drive down their wages.

In the European context, Dustmann et al. (2005) found heterogeneous effects of immigration on native wages across different skill groups. Their research revealed a notably more significant negative impact on the wages of low-skilled native workers compared to their highly skilled counterparts. Similarly, Dustman et al. (2017), examining a local labor supply shock in a German-Czech border region, uncover a moderate decline in German wages alongside a substantial negative response in local native employment.

Dorn and Zweimüller (2021) highlighted the obstacles to migration and labor market integration in Europe, particularly focusing on language and cultural barriers, and explained that Europe's significant linguistic diversity makes it difficult for immigrants to secure employment in another country's labor market. The European Union alone has 24 official languages, and the non-EU members of the common labor market add another three. A lack of proficiency in the destination country's language not only limits immigrants' ability to find jobs quickly but also reduces productivity in the workplace and social inclusion. Building upon this notion, Chiswick and Miller (2015) emphasized that poor language proficiency has a sizable negative effect on the labor earnings of immigrants.

In the literature, a significant body of studies has focused on assessing the impact of forced immigration on native populations. For instance, research conducted in Turkey and Jordan (Ceritoglu et al., 2017; Tumen, 2016) shows that the influx of migrants and refugees leads to a reduction in the employment and wages of low-skilled natives. Borjas and Monras (2017) in turn provide insight into the persistent negative effects of exogenous refugee supply shocks on the labor market prospects of native workers in receiving countries. However, they also find that these shocks can affect different skill groups in varying ways, occasionally resulting in benefits for complementary native workers.

Several recent studies shed light on the impact of Venezuelan immigration on the Colombian labor market. Both Delgado-Prieto (2024) and Caruso et al. (2021) find negative effects on native Colombian wages resulting from the Venezuelan mass migration. Further contributing to this understanding, Bahar et al. (2021) focus on the formal employment sector and find negative, albeit negligible, effects of Venezuelan immigrants on highly educated and female Colombian workers. Similarly, Monras (2020) suggests that native low-skilled wages in the U.S. decrease in areas experiencing high immigration from Mexico. Additionally, Edo (2020) observes that an increase in labor supply due to the inflow of repatriates to France after Algerian independence in 1962 led to a decrease in regional wages.

Studies reporting positive effects of immigration on native wages, namely by Ottaviano and Peri (2006, 2008), Peri and Sparber (2009), D'Amuri et al. (2010), and Martins et al. (2018), highlight in particular the complementary nature of immigrant and native labor. These authors argue that by filling existing labor market gaps, immigrants contribute to productivity and economic growth, leading to higher wages for native workers. These studies emphasize the potential positive spillover effects of immigration on the overall economy, such as increased consumer demand or job creation in sectors benefiting from immigrant labor. In this context, Ortega and Peri (2009) highlight the potential positive impact of immigrants on per capita income, physical capital accumulation, and total factor productivity in destination countries, by inducing technological shifts and changes in the optimal organization of production, as illustrated by Lewis (2005). Similarly, Ottaviano et al. (2013) argue that the increasing presence of migrants in certain regions could influence the international organization of production for firms.

In contrast, influential studies conducted by Card (2001, 2005) in the United States found a limited impact on native wages overall, with small positive or negligible effects observed. Dustmann et al. (2013), for their part, suggest that UK immigration slightly seems to have increased the average wage of native workers, although the wage response varies across the distribution, with a decline below the twentieth percentile and a modest gain in the upper ranks. Likewise, Ortega and Verdugo (2014) show that immigration in France raised the wages of French workers by facilitating the reallocation of native workers to better-paying occupations. In a different context, Groeger et al. (2024) find in their research on Venezuelan immigration that higher local influxes led to lower crime rates and positive labor market outcomes for Peruvians, including increased employment rates, incomes, and expenditures.

But while previous studies have highlighted both positive and negative effects of immigration on host countries' labor markets, some research suggests no effect. For example, Santamaria (2020) finds that the influx of Venezuelan refugees into Colombia has no discernible effect on the employment and wages of natives. Similarly, Boruchowicz et al. (2021) observe no significant impact on employment in Peru following the migration of Venezuelans.

Undoubtedly, the vast majority of studies in the literature have primarily focused on measuring the impact of immigration on native wages based on educational attainment, with only a minority having examined the role of occupational characteristics and skill levels. In a recent study by Sharpe and Bollinger (2020), who have constructed occupational groups using skill data from the O*NET database, argue that native workers at the lower end of the skill distribution, in direct competition with immigrant workers, tend to experience negative wage effects in the presence of immigrants. This suggests that the presence of immigrants in low-skilled occupations may lead to wage suppression for native workers in similar occupations. On the other hand, the situation appears to be reversed for native workers at the higher end of the skill distribution. These findings imply that natives in highly skilled occupations may benefit from the presence of immigrants, potentially experiencing positive wage effects.

By focusing on skill groups and O*NET-based occupations, our inquiry follows the latter strand of research. The goal is therefore to shed further light on the interaction between native and immigrant workers within specific occupational categories. While there are other studies utilizing a similar approach, our emphasis lies in using the skill requirements of occupations to construct labor market subsets with a greater degree of homogeneity.

3. Data

Data sources

Our primary data source is a detailed panel dataset collected annually by the Portuguese Ministry of Employment, known as Quadros de Pessoal (QP). This dataset covers all employees in private enterprises and spans the period from 2010 to 2019. It contains comprehensive information provided by employers, including firm-level industry affiliation and the number of employees as well as worker-level information such as the job title, earnings, gender, age, schooling level, years of service (i.e., tenure), and country of origin, a key variable in our inquiry.

Skill group

In order to construct skill groups for our analysis, we consider both work experience and educational level. Following Borjas (2003), we calculate the measure of potential labor market experience as the difference between age and the entry age for employees in a particular schooling group (age - A_T), where A_T represents the entry age adjusted for the number of school years (i.e., age - 6 - school years).

The educational levels of Portuguese workers, as detailed in the QP dataset, are categorized into four distinct groups: individuals with four years or less of full-time school education or its equivalent; workers with five to nine years of full-time school education or its equivalent; employees who have attained secondary education; and those who have graduated from tertiary education institutions or obtained degrees from equivalent institutions such as polytechnics. Each educational group is further disaggregated into eight experience sub-groups, with each subgroup spanning a five-year interval (1 to 5 years of experience, 6 to 10 years, 11 to 15 years, ..., up to 36 to 40 years.

Descriptive Statistics

Table 1 presents the summary raw statistics. Note that during the data cleaning process we excluded all observations with non-strictly positive values for earnings. Additionally, workers with undefined education levels and those aged under 18 or over 65 were dropped from the analysis. Following the methodology of Cardoso and Portela (2009), gross monthly earnings are derived by adding the base wage (gross pay for normal hours of work), seniority-indexed components of pay, and other regularly paid components. To account for inflation, wages were adjusted using the consumer price index, and the values underwent winsorization at the 1st and 99th percentiles. As can be seen in the table, the final dataset comprises 19.29 million worker-year observations, with an average of 2.6 million individuals per year.

Regarding the worker-level statistics, workers are classified into natives (i.e., those born in Portugal) and non-natives (immigrants). The demographic composition reveals that immigrants (both male and female) constitute 5.57% of the total. The proportion of non-native workers in total employment increased from 5.57 percent in 2010 to 7.03 percent in 2019. The average age of immigrants is 37 years, highlighting a relatively young labor force; non-immigrants in turn exhibit an average age of 39 years. Immigrants also tend to earn lower wages than natives and have lower levels of education. It is not surprising either that immigrants have fewer years of labor market experience, indicating that they may have recently entered the workforce or faced limited opportunities for career advancement. These findings duly confirm prior research conducted by Chiswick et al. (2008), Martins et al. (2018), and Adsera (2005), inter alia. Appendix Table A. 1 shows the distribution of male immigrants by skill group.

[Table 1 near here]

Occupation groups

In our analysis of occupational groups, we rely on the Portuguese Classification of Occupations CPP (2010) to categorize occupations at the four-digit level. However, since the Portuguese register data lacks information on professional characteristics and requirements, we turn to the Occupational Information Network (O*NET) survey (version 27) provided by the U.S. Department of Labor.

The O*NET survey is a comprehensive database that provides a wealth of information on employee and job characteristics based on surveys of workers, employers, and job experts. By linking the O*NET data to occupations, we obtained a total of 374 CPP-O*NET unique occupations for our analysis. While the O*NET survey covers six distinct areas, we focused on four surveys that aligned with the approach taken by Sharpe and Bollinger (2020): workers' skills, knowledge, abilities, and work activities. The skills domain encompasses developed capacities that facilitate learning and the acquisition of knowledge, such as effective communication (e.g., conveying information through speaking). The knowledge domain pertains to organized sets of principles and facts that apply to general domains, such as mechanical knowledge involving machines, tools, repairs, and maintenance. The ability domain addresses persistent attributes of individuals that influence performance, such as verbal ability for problem-solving using verbal information. Finally, work activities encompass tasks that are common across a wide range of occupations and are performed in various job families and industries. An example of a work activity is assisting and caring for others, which involves providing personal assistance, medical attention, emotional support, or other forms of care to coworkers, customers, or patients (O*NET Content Model, 2022). For a detailed list of the variables used in our analysis, please refer to Appendix Table A. 2.

Following Peri and Sparber (2009), we adopt the notion that occupations can be distinguished by two occupation-specific indices related to task intensity: manual task intensity and communicative task intensity. To group individual occupations based on their relative communicative-to-manual task intensity, we utilize the O*NET dataset. Specifically, for each occupation (j) is assigned an importance value (I) ranging from 0 to 5 and a level value (L) ranging from 0 to 7 for each feature of four domains of O*NET (k). Thus, for each occupation (j) and feature (k), we have level values represented as $L_{j,k}$ and importance values represented as $I_{j,k}$. we then compute the mean importance value ($\bar{I}_j^{comm}$ and $\bar{I}_j^{man}$) and the mean level value ($\bar{L}_j^{comm}$ and $\bar{L}_j^{man}$) for each occupation. Subsequently, we generate task-intensity values for manual tasks (TS_j^{manual}) and communicative tasks (TS_j^{comm}) by multiplying the corresponding importance value and level value. These values are known as skill ratios. Specifically, the skill ratio for each profession is calculated as the ratio of communicative task intensity to manual task intensity ($\frac{TS_j^{comm}}{TS_j^{manual}}$). These skill ratios allow us to redefine our occupational groups based on their relative task intensities. Finally, to ensure the same number of qualification groups as in Borjas (2003), we construct a four-group occupational classification based on the task-intensity distribution.

Figure 1 comprises four panels, each displaying the correlation between years of experience and immigrant penetration in various skill groups from 2010 to 2019. The horizontal x-axis represents the potential years of experience among foreign-born workers, while the vertical y-axis illustrates the proportion of immigrants relative to the total employment within each skill group.

Panel A represents the lowest quartile of communicative to manual job intensity, primarily consisting of blue-collar positions characterized by manual labor and minimal skill requirements. Progressing from Panel A to Panel D, there is a noticeable increase in communicative to manual job intensity, indicating a transition from low-skilled to highly skilled occupations. Consequently, Panel D signifies the highest quartile, predominantly comprising white-collar professions that demand advanced skills and involve more communicative tasks.

The share of immigrants remains relatively consistent over time, with consistent levels observed across the years, except for 2019. As evidenced by the data presented in Table 1, in 2019, there is a notable increase in immigrant representation, surpassing levels seen in previous years.

Across all four panels, a clear trend emerges: the proportion of immigrants declines as years of experience increase. In other words, as individuals gain more experience in the workforce, there is a corresponding decrease in the representation of non-native individuals. This observation suggests significant shifts in the composition of the labor market over time, potentially leading to heightened competition between native workers with lower potential labor market experience and immigrants.

[Figure 1 near here]

Figure 2 displays the relationship between changes in the residualized immigrant share and changes in the residualized log native wages across different occupation-experience groups. The regression model incorporates controls for year, occupation, and experience fixed effects. On the x-axis, we observe the change in the residualized immigrant share, while the y-axis represents the change in the residualized log native wages. The graph reveals a positive association between wage growth and the influx of immigrants into specific skill groups. Specifically, a 1 percentage point (p.p) increase in the share of immigrants within an occupation-experience group is associated with a 0.393 percentage point (p.p) increase in native wages (standard error of 0.148).

[Figure 2 near here]

4. Modeling

4.1 The elasticity of substitution between native and non-native labor inputs

The elasticity of substitution between labor inputs is a concept derived from neoclassical input demand theory, which seeks to determine the extent to which two labor inputs can be substituted or complemented in the production process. Borjas (1999), for example, argues in favor of perfect substitutability, in which case, say, a positive supply shock from an increase in immigrant workers would negatively impact the wages of both local and foreign-born workers. In contrast, Dustmann et al. (2013), Ottaviano and Peri (2012), and Peri and Sparber (2009) argue that the assumption of perfect substitutability may not mirror reality.

The aim is to test the hypothesis of perfect substitution as proposed by Borjas et al. (2012). This involves examining the relationship between the logarithm of relative wages for immigrants in a specific skill group and the logarithm of relative immigrant supply in the same group. We apply the CES (Constant Elasticity of Substitution) framework to the total labor input within each skill group *i*, experience group *j*, and year *t* $[\psi_{ijt}(L_{ijt}^F)^\lambda + (1-\psi_{ijt})(L_{ijt}^D)^\lambda]^{\frac{1}{\lambda}}$, an Armington aggregator of the total supply of foreign-born (L_{ijt}^F) and native-born (L_{ijt}^D) workers. ψ_{ijt} is a technology parameter that reflects the relative productivity of foreign-born and native-born workers, subject to variation over time. λ is a substitution parameter, determining the curvature of the substitution possibilities between foreign-born and native-born workers. Here, *n* indicates the nationality group, with *n* being either *F* (foreign-born) or *D* (native-born). Using this CES framework and drawing on the methodologies of Borjas et al. (2012, p. 201) we establish the following model:

$$\ln\left(\frac{w_{ijt}^{F}}{w_{ijt}^{D}}\right)=\emptyset_{ijt}-\frac{1}{\sigma_n}\ln\left(\frac{L_{ijt}^{F}}{L_{ijt}^{D}}\right) \qquad [1]$$

where $\emptyset_{ijt} = \ln\left[\frac{\psi_{ijt}}{(1-\psi_{ijt})}\right]$ and $\sigma_n = \frac{1}{(1-\lambda)}$ denotes the elasticity of substitution. w_{ijt}^{F} and w_{ijt}^{D} represent the wages of foreign-born and native-born workers, respectively. A higher σ_n, implies a greater degree of substitution between immigrants and natives.

To examine the extent of substitution between immigrants and natives, we estimate $\emptyset_{ijt}$ separately for each skill group, considering different specifications that include skill group effects and interactions between skill groups and time dummies. Table 2 presents the estimated inverse elasticity of substitution between immigrants and natives for various subsamples, using two skill group definitions: the education-experience approach and the occupation-experience approach. The subsamples include all workers, only full-time workers, and further breakdowns by gender, such as only men and men and women combined. These estimations are conducted with the use of two weights. This choice is motivated by the concern that there could be variations in the sampling error of the wage ratio, which serves as the dependent variable across different observations. The first weight, derived from Ottaviano and Peri (2012; hereafter, OP), utilizes total employment in the skill cell (education-experience/occupation-experience). Borjas et al. (2012), on the other hand, advocate for the use of the inverse of the sampling variance for an observation as the appropriate weight.

Additionally, there is the question of which fixed effects to incorporate into the regression model. To address the issue of changes in within-group skill composition, we follow Borjas et al. (2012) by including skill-group and period fixed effects. Columns (2) and (6) of Table 1 introduce the period fixed effects, with the addition of interaction terms: education/occupation × experience in columns (3) and (7); education × year and experience × year in columns (4) and (8). We utilize robust standard errors clustered by the education-experience/education-experience group.

In column (1), we first analyze the elasticity estimates for the education-experience classification. In column (2), we extend this analysis by including time fixed effects. In both columns, our estimation results indicate a rejection of the CES framework. While the implied elasticities of substitution are mostly statistically significant, they exhibit signs that are inconsistent with the theoretical expectations.

In column (3), when we expand the model to include education-experience interactions and restrict our analysis to male workers (row 1), we use the OP weight and find a coefficient of -0.146 (standard error = 0.024, which implies an elasticity of substitution of 6.85. The literature does not provide specific guidance on the size of the elasticity of substitution between immigrants and natives. However, we rely on existing studies which indicate that a regression coefficient of zero ($-\frac{1}{\sigma_n}$ = 0) represents perfect substitutes (Card and Lemieux 2001, p. 711; Borjas et al. 2012, p. 205). Therefore, an elasticity of 6.85 indicates complementarity between immigrants and natives. Using an alternative weight based on the inverse of the sampling variance of the dependent variable, in row (2), the coefficient for $-\frac{1}{\sigma_n}$ is -0.133 for men and -0.116 for the combined sample of men and women (row 4), both statistically significant. In row (6), the coefficient remains similar at -0.145 (standard error = 0.023).

In column (4), row (2), incorporating controls for year–education group and year–experience group interactions yields a coefficient of -0.036 (standard error 0.044) for male workers. According to Sharpe and Bollinger (2020, p. 4), which define an implied elasticity of substitution of 37 as indicating imperfect substitution, an elasticity of 28 similarly indicates imperfect substitution between immigrants and natives. Additionally, the R-squared value increases progressively from column (1) to column (4), suggesting that the inclusion of time and skill group dummies improves the model.

When analyzing occupation-experience groups in columns (5) to (8), the key coefficients are similar to those obtained in columns (3) and (4). In column (8), after adding time fixed effects and skill interaction terms, the coefficient for male workers, weighted by the inverse of the dependent variable's sampling variance, is -0.125 (standard error 0.046). This coefficient is statistically significant, indicating an elasticity of substitution of 8. Similarly, for both male and female workers combined, the coefficient is -0.108 (standard error 0.042) and also statistically significant. This indicates that within occupation-experience groups, immigrants and natives complement each other conspicuously. Collectively, these results underscore the importance of including Education/Occupation × experience fixed effects are required, otherwise one gets counterintuitive results.

[Table 2 near here]

4.2 A structural approach to immigration and native wages

The empirical framework used in this analysis is based on the assumption that the Portuguese labor market can be treated as a single national market, following the approach of Borjas et al. (1997) and Borjas (2003). This assumption is supported by three key aspects: firstly, immigrants tend to settle in regions with higher wages (it is commonly observed that immigrants choose to move to areas with better economic opportunities, including higher wages), an indication that the labor market is not segmented across regions in terms of wages. Secondly, native workers tend to move away from areas settled by immigrants, which means that in response to immigrant inflows, native workers often choose to relocate to regions where there are fewer immigrants. This behavior indicates that there is a spatial sorting of workers based on immigration patterns. Finally, employers may seek to take advantage of the availability of a cheaper labor force provided by immigrants, potentially leading to changes in wages and employment (Grossman, 1982; Altonji and Card, 1991).

To address these issues, the empirical model categorizes workers into distinct skill groups according to their job functions and years of experience. Drawing on the methodologies of Borjas (2003) and Card (2001), the primary analysis utilizes a wage equation to estimate the influence of immigration on native wages. This framework facilitates an evaluation of how the presence of immigrants impacts the earnings of native workers within these skill groups. The empirical model can be described as follows:

$$w_{ijt} = \beta s_{ijt} + \theta_i + \varphi_j + \tau_t + (\theta_i * \tau_t) + (\varphi_j * \tau_t) + (\theta_i * \varphi_j) + \varepsilon_{ijt} \qquad [2]$$

where w_{ijt} denotes the mean of the log wages of natives in occupation group i and experience group j at time t; s_{ijt} is the foreign-born share of the labor force in a skill group (i,j) at time t. The coefficient of interest, β, measures the impact of immigration on native wages. It captures how changes in the foreign-born share of the labor force in a specific skill group affect the wages of native workers in that skill group. The immigrant share in the labor force is given by $s_{ijt}=\frac{M_{ijt}}{M_{ijt}+N_{ijt}}$, where M_{ijt} denotes the number of immigrants in cell (i,j,t), and N_{ijt} is the number of natives. The argument for including the additive fixed effects in our model is to control for average wages across occupation group (θ_i), experience group (φ_j), and year (τ_t). The interaction terms ($\theta_i * \tau_t$) and ($\varphi_j * \tau_t$) absorb a large part of the variation in the impact of occupation and experience on average wages. Finally, by interacting occupation group and experience group fixed effects ($\theta_i * \varphi_j$), we can examine whether the labor market impact of immigrants can be identified using time variation within occupation-experience cells.

It is easier to interpret this coefficient by converting it to an elasticity that gives the percent change in wages associated with a percent change in labor supply. Following Borjas (2003, p. 1349), the wage elasticity is given by:

$$\frac{\partial \log W_{ijt}}{\partial m_{ijt}} = \frac{\beta}{(1+m_{ijt}{}^2)} \qquad [3]$$

where m_{ijt} is the percentage increase in the labor supply of immigrants in occupation group i (i=1, ..., 4), experience group j (j= 1, …, 8) and time period t (t= 2010, …, 2019).

Generating an instrumental variable

The regression presented in equation (2) may be flawed due to the endogeneity of the immigrant share variable. Immigrants tend to settle in regions with substantial enclaves of compatriots, driven by the influence of existing immigrant networks. These networks play a crucial role in the location decisions of prospective immigrants, as they ease the job search process, facilitate cultural assimilation, and provide vital support and assistance (Munshi, 2003). Consequently, the presence of these networks can significantly impact the distribution of immigrants, introducing endogeneity into the analysis.

To address the problem of this source of endogeneity, we employ the use of an instrumental variable (IV) in a two-stage least squares regression model (2SLS). Drawing on Card (2001), we introduce a shift-share instrument that integrates the historical share of the immigrant population from each country of origin with the current national inflow of immigrants from those countries. As per Card (2001), the shift-share instrument is defined as follows:

$$\widehat{\mathrm{IM}}_{\mathrm{ijt}} = \sum\nolimits_{0} \frac{\mathrm{IM}_{\mathrm{o,ij,2010}}}{\mathrm{IM}_{\mathrm{PT,o,2010}}} * \mathrm{IMM}_{\mathrm{ot}} \qquad [4]$$

where (i) $\frac{IM_{o,ij,2010}}{IM_{PT,o,2010}}$, is the fraction of immigrants from country *o* who belongs to skill group ij (occupation-experience group) in year 2010, at the beginning of our period of observation, following the methodology that allows us to analyze subsequent changes relative to this initial distribution. Here, $IM_{o,ij,2010}$ refers to the total number of immigrants from country *o* within skill group ij (occupation-experience group) in 2010, and $IM_{PT,o,2010}$ is the total number of immigrants from country *o* living in Portugal in the same year (ii) $IMM_{o,t}$, given by the number of new arrivals at national level from of origin *o* from 2010 to 2019. After aggregating the different country origins, the instrument is constructed to predict the number of immigrants expected within a specific skill group.

5. Results

Table 3 presents the estimates of β in different specifications. The first column focuses on the education-experience groups, where a four-group classification, based on the level of schooling, is used: individuals with 4 years or less of formal education, workers with 5 to 9 years of education, workers who have secondary education, and workers with tertiary degrees. The second column examines the occupation-experience groups, where the classification is based on occupations and experience levels as described in Section 3.4. The definitions of variables are fully provided in Appendix Table A. 3.

In Table 3, the results are also presented in five separate specifications (rows). The first row presents the basic estimation, weighted by the number of observations used to compute the average wage for male workers within each cell. The second row shows the same regression as the first but without weights. Given that the primary explanatory variable is the immigrant share within a skill group, an increase in s_{ijt} could result from either an increase in immigrant labor supply or a decrease in native labor supply. Therefore, the estimates in the third row reflect the effect of s_{ijt} while holding the native labor supply constant, as discussed by Sharpe and Bollinger (2020).

In the fourth row of the analysis, a different approach is taken by introducing a new dependent variable, which calculates the mean of the residualized log wage within each cell. This method, inspired by Jaeger et al. (2018), allows for a more comprehensive analysis by considering additional factors that could affect wages beyond those accounted for in the initial estimation. This approach is particularly valuable in addressing composition bias, which arises when shifts in the makeup of the workforce—such as changes in skills, education, or experience—impact observed average wages. For instance, if the workforce becomes more educated or experienced over time, average wages might appear to increase even if the underlying wage structure remains unchanged. To address this bias, residual wages are employed. Residual wages isolate the portion of wage changes that cannot be directly attributed to changes in observable characteristics of the workforce. By removing the effects of observed factors like skills, education, and experience from the wage equation, residual wages capture the unexplained variations in wages that may stem from factors not directly observable. Therefore, by focusing on residual wages, we gain a clearer understanding of how wages are changing independently of shifts in the composition of the workforce. This approach helps to mitigate the influence of composition bias and allows for a more accurate assessment of genuine trends in wage dynamics.

In row (5), the immigrant share, s_{ijt}, is redefined to include both male and female labor force participants. In rows (6) and (7), we address the potential endogeneity of the migrant share by using a fictional share computed through Card (2001) methodology. We implement the two-stage least squares (2SLS) approach, employing the *ivreg2* in Stata, which is a single-equation instrumental-variables regression command as described in Baum et al. (2010).

According to Borjas (2003), elasticity is defined as the measure of the percent change in wages resulting from a percent change in labor supply. The corresponding elasticities are provided in square brackets. Equation (3) suggests that the wage elasticity, evaluated at the mean increase in immigrant supply, can be derived by multiplying β by 0.46.

In the first column, using the traditional education-experience classification, the estimated coefficient is negative and statistically significant, implying that an increase in the immigrant share has a dampening effect on native wages. The estimated elasticity, shown in the bracket as -0.512 (-1.114 × 0.46), suggests that, on average, a 1% increase in the share of immigrants within the education-experience group is associated with a 0.512% decrease in native wages, holding all else constant. This finding confirms the results obtained by Sharp and Bolinger (2020) and Card (2001), who found that immigrant inflows reduce native wages.

Downgrading was observed in various studies, including those by Eckstein and Weiss (2004), Dustmann et al. (2013), and Dustmann and Preston (2012), among others. Dustmann et al. (2016) define downgrading as the scenario where immigrants receive lower returns for their skills compared to natives when these skills are acquired in their home country. They further explain that downgrading poses a challenge when categorizing immigrants into specific education-experience groups for analysis and leads to a bias in the estimates obtained from the national skill-cell approach. However, the direction of this bias remains uncertain and depends on the observed immigration shocks within education-experience groups. Thus, the negative results obtained in column (1) may suggest that immigrants in these groups are subject to downgrading in the labor market.

We report different specifications, varying the definition of the skill group, specifically occupation-experience groups, by the distribution of the communicative-to-manual task intensity ratio in column (2). The regression outcomes reveal a positive and statistically significant coefficient associated with the main variable of interest, the immigrant share variable. This implies that the share of immigrants has served to increase the wages of native workers. Specifically, on average, a 1% increase in the share of immigrants within the occupation-experience group will increase native wages by 0.357%. This finding of a positive effect of immigration on outcomes for natives indicates that immigrants and natives with similar levels of work experience tend to complement each other within these cells This conclusion, supported by the findings in Table 2, aligns with the findings of Ottaviano and Peri (2006), Dustmann et al. (2008), and Barrett et al. (2011).

The two contradictory results align closely with the findings of Barrett et al. (2011). Barrett and colleagues found a negative impact on wages, with a coefficient of -0.178 (0.456) when using the education-experience approach. However, they observed a positive impact, with a coefficient of 0.631 (0.210), when they repeated the analysis using occupation-based skill cells. The authors explained that their method does not aim to assess the effect of immigration on the average native worker's wage. Instead, it examines how different skill groups are affected. Since the average education-based skill group differs from the average occupation-based skill group, contradictory results are possible in principle. Additionally, drawing on Dustmann et al. (2016), these two approaches identify distinct and incomparable parameters, contributing to the ongoing debate surrounding the wage effects of immigration in the literature. While the education-experience approach assesses the impact of immigration across different experience groups within education categories, the occupation-experience approach evaluates it by examining the influence of immigration within specific occupational categories across various experience levels. Therefore, focusing solely on education might suggest that immigration reduces wages, while concentrating on occupations might indicate that it increases wages. These inconsistent findings underscore the risk of spurious correlations, highlighting the need for robust analysis to ensure the results are reliable.

In the second row, when we remove the weighting of each cell, the coefficient for the education-experience group decreases by half, while the coefficient for the occupation-experience group doubles.

This difference in coefficient changes can be attributed, at least in part, to the unequal sizes of the groups. Larger groups naturally exert a greater influence on the estimated coefficients, potentially leading to larger coefficients if these groups exhibit stronger relationships between the predictors and the outcome. While the unweighted analysis may be influenced disproportionately by larger groups, the weighted regression addresses this bias by appropriately weighting each observation based on the group size. This adjustment results in more balanced and accurate coefficient estimates.

The third row of Table 3 incorporates the log of the native workforce size in each cell (i, j, t) as a regressor. Because the key explanatory variable is the immigrant share of total employment within a skill group, an increase in $\mathrm{s_{ijt}}$ could result from either a rise in immigrant labor supply or a reduction in native labor supply. As such, the estimates in row (3) report the impact of s_{ijt} while holding native labor supply constant. This approach allows us to disentangle the influence of changes in immigrant and native labor supply within skill groups. The findings in this specification are consistent with those in the first row, reaffirming the significant impact of immigration on native workers' wages.

To assess the composition effects, we use the log of residualized wages in row (4), following Sharp and Bollinger (2020). In column (1), we observe a contrasting result: the coefficient becomes insignificant and, unlike the other rows, it is positive. This indicates that, when accounting for composition effects, the impact of immigration on wages within the education-experience group is not statistically significant and even suggests a positive relationship. In column (2), the results are statistically significant but marginally lower than the findings in row (1).

The specification in row (5) includes both male and female workers when measuring the impact of immigrant share. Since women often have more discontinuous careers compared to men, classifying them into age-based experience cells may be less accurate (Borjas, 2003). Despite this potential issue, the results in both columns show only a slight increase, and the significance remains robust. This indicates that the inclusion of both genders does not substantially alter the estimated impact of immigration on native wages.

Considering the endogeneity of the immigrant share, as highlighted by Borjas (2003), is crucial. The allocation of immigrants across different labor markets is not random, which can bias the results at the national level. To address this issue, rows (6) and (7) utilize the shift-share instrument and a two-stage least squares (2SLS) estimation approach, focusing on occupation groups. In row (6), the estimated elasticity is larger in magnitude compared to the results in row (1). This suggests that attenuation bias, potentially caused by measurement errors, significantly influences the estimates, leading to a downward bias in the OLS estimation relative to the IV estimator. Specifically, the 2SLS estimate indicates that, on average, a 1% increase in the share of immigrants within an occupation-experience group results in a 0.629% increase in native wages. This finding underscores the importance of addressing endogeneity to obtain more accurate estimates of the impact of immigration. In row (7), we include the native labor force as a regressor. The coefficient is 0.728 (with a standard error of 0.266), which is similar to the result in row (1). This regularity suggests that the relationship between immigrant share and native wages is robust to the inclusion of native labor force size in the model. Overall, these results reinforce the positive impact of immigration on native wages while also highlighting the need to account for endogeneity to avoid biased estimates.

[Table 3near here]

Using an instrumental variable approach helps address endogeneity issues, but overcoming the weak instrument problem can be challenging. An instrumental variable needs to fulfill two requirements: it must be correlated with the endogenous variables (relevance) and orthogonal to the error process (validity). Testing the relevance of the instrumental variables is typically done by examining the F-statistic of joint significance in the first stage regressions. To this end, we conduct tests for underidentification, weak identification, and overidentification. The results from the first-stage of the 2SLS implementation (in Table 3) are given in Table 4.

In columns (1) and (2), the dependent variable is the share of immigrants. To demonstrate the relevance of the constructed instrumental variables, we use the Kleibergen and Paap (2006) rank LM statistic, which is robust against heteroskedasticity and autocorrelation. This test consistently rejects the null hypothesis of underidentification, confirming the instrument's relevance. To further support this, we perform weak identification tests using the Cragg-Donald Wald (1993) and Kleibergen-Paap (2006) rank Wald F-statistics. The null hypothesis for these tests posits that the instrumental variable is weakly correlated with the endogenous variables. The high F-statistic from the Cragg-Donald Wald test indicates a strong correlation between the instrumental variable and the endogenous variable. Additionally, the Kleibergen-Paap rank Wald F-statistics consistently surpass the critical thresholds established by Stock and Yogo (2005), as shown in Table 4. Lastly, the overidentification test by Hansen (1982) does not reject the null hypothesis, suggesting no correlation between the instruments and the error term. These results collectively underscore the significant role of the instrumental variables in explaining the endogenous share of immigrants.

[Table 4 near here]

To further test the robustness of the findings, we employ in Table 5 finer classifications based on the communicative-to-manual skill ratio, as suggested by Sharp and Bollinger (2020). The goal is to determine if the results remain consistent under different conditions. In column (1), we utilize the mean log wages, while in column (2), we employ the log of residualized wages. The table also displays the results for different groupings: sextiles in row (1), deciles in row (2), and ventils in row (3). By comparing the estimates obtained from these different groupings to the baseline values in the first row, we can assess the stability of the main estimation in Table 3 across various classification schemes.

Across the finer groupings, the results consistently indicate positive but statistically insignificant elasticities, which are lower than those presented in Table 3. An exception is found in the sextiles analysis presented in column (2), where the coefficient is small but statistically significant. These findings suggest that the estimated elasticities derived from the occupation-experience specification with quartile groupings are consistently larger in magnitude compared to those obtained from the other grouping analyses, potentially indicating a stronger relationship that might be overlooked in finer groupings. These findings suggest that using quartile groupings in the occupation-experience specification might provide a more accurate and appropriate analysis of the impact of immigrant shares on native wages within skill groups.

[Table 5 near here]

5.1 Do they resemble us?

Thus far, our analysis has focused on assessing the impact of immigrants on native wages within occupation-experience cells, where immigrants and natives directly compete in the labor market. Table 2 indicates that immigrants and natives with similar levels of work experience tend to complement each other within these cells, as supported by the findings in Table 3. However, when we classify workers based on education levels, this complementary relationship is not as apparent. The results from presented in Table 3 indicate immigrants and natives with similar education and experience levels are likely competing for the same jobs, resulting in increased competition and lower wages for natives.

This observation prompts us to consider an alternative approach based on education classification, after Sharpe and Bollinger (2020). They suggest that if immigrants choose occupations based on favorable labor market conditions, it could bias the estimates upward in Tables 2 and 3. Thus, we adopt an education-based classification to investigate whether immigrants resemble natives and, if so, how this resemblance affects native wages. If immigrants and native workers exhibit complementarity, suggesting that they possess similar skills, education, and experience, our education-based classification could reveal how they fill labor shortages, potentially leading to higher wages for native workers. Conversely, if immigrants and natives show substitution effects due to high similarity and direct competition for the same jobs, our classification could uncover how this competition impacts wages, especially if immigrants are willing to work for lower wages or possess similar skills but accept lower pay, potentially driving down native workers' wages. This approach aims to shed light on the mixed results observed in Table 3 and in the existing literature.

The model utilized to examine individual nativity employs a probit framework in which the nativity status variable Y is a dichotomous variable taking the value of 1 if the individual in the labor force is an immigrant as follows (for males and females in separate samples):

$$P_r\ (Y_i = 1|X_i) = \Phi(\beta X_i). \qquad [4]$$

The model assumes that the relationship between the predictors and the probability of being a native follows a normal distribution, denoted by the cumulative distribution function Φ of the standard normal distribution. Estimation involves determining the vector of coefficients β, which signifies the impact of each explanatory variable X_i. These variables include demographic characteristics such as education levels, a quartic term to accommodate potential experience variations, and an extensive range of education-by-demographic interactions. To test the nativity status, the model additionally incorporates the influence of the occupation group on and geographic location. Specifically, it examines how occupation group impacts nativity status and assesses whether individuals residing in the capital city, Lisboa, have different probabilities of being native compared to those in other geographic locations. These effects on the probability of the binary outcome are estimated using maximum likelihood estimation.

The results presented in Table 6 illustrate the monthly wages and demographic attributes of native workers, categorized into four quartiles (denoted Low, Medium, High, and Very High Competition respectively). The quartiles reflect the degree of similarity between foreign-born workers and natives, from Low to Very High. The analysis encompasses the entire sample, and we chose to showcase the findings for the year 2016 as an illustratation. The results of other years are available upon request.

[Table 6 near here]

Firstly, younger workers tend to experience heightened competition from foreigners, leading to a decrease in potential experience as competition intensity increases. In the Low Competition case, workers have an average of 26 years of potential experience, whereas in the fourth case (Very High), this decreases to 16 years. This pattern indicates a decline in potential experience as competition intensity rises, aligning with findings by Borjas (2003) and Card (2001) that younger native workers face increased competition from foreign workers. Secondly, in the quartile with Low Competition, approximately 5% of workers live in Lisboa, whereas in the High competition quartile this percentage declines to 74%. This finding indicates a noticeable increase in the proportion of workers living in the capital as competition intensity increases. Thirdly, there is a gradual upward trend in the percentage of workers holding full-time contracts, irrespective of their level of competition with foreigners. This suggests a general inclination among native workers towards securing full-time employment contracts. Fourthly, in the Low Competition quartile, there is a significant presence of highly educated individuals, with 39% holding tertiary education qualifications. Conversely, a smaller proportion of workers, 18%, possess 4 years or less years of education. In the High Competition quartile, there is a notable shift in the distribution of education levels. The percentage of workers with tertiary education decreases markedly to just 2%, indicating a substantial decline in highly educated individuals. Instead, the proportion of workers with 5-9 years of education increases, with the majority (60%) falling into this category. This suggests a dominance of individuals with low level education in the high competition quartile, while the percentage of tertiary-educated individuals decreases. Finally, the results suggest that as competition intensity increases, the proportion of workers in blue-collar jobs (occupation group 1) rises significantly from 28.03% to 40%. This shift suggests a greater concentration of workers in blue-collar roles in more competitive environments. Conversely, the proportion of workers in white-collar jobs (occupation group 4) decreases dramatically from 41.39% in Low Competition to just 11.73% in Very High Competition quartile. This suggests that higher competition is linked to a reduction in the share of workers in white-collar positions. The increasing presence of workers in blue-collar jobs, along with the decreasing presence in white-collar roles, suggests a shift towards more competitive, less specialized job markets where blue-collar jobs predominate. This trend may reflect the fact that blue-collar jobs are more susceptible to competition from immigrant workers, who might be more willing to accept lower wages for these types of positions.

Our main empirical strategy now is to estimate model (2) using, alternatively, the average log monthly wage of demographically comparable native workers in a given competition quartile within a specified education-experience group as the dependent variable. We report the result of this estimation in Table 7. Each column presents the results of a separate regression, which includes time fixed effect, workers' educational attainment (categorized into four levels) and their potential experience (8 groups). Additionally, the interaction of education fixed effects with time, experience group fixed effects with time, and an interaction of education and experience are incorporated.

[Table 7 near here]

The results from Table 7 indicate varying effects of competition intensity on wages across different columns. In the Low Competition (Medium) quartiles, where natives least (medium) resemble immigrants, the results for the variable of interest s_{ijt} is positive and statistically significant, mirroring those in Table 3, column (2), albeit with increased magnitudes. In column (3) the High Competition quartile, the coefficient is still positive, although the coefficient is not statistically significant. However, in the Very High competition quartile, the result turns negative and becomes insignificant. In the last two columns, the same pattern appears. In the top 50% competition quartile, which combines the High and Very High competition quartiles, we observe a negative and insignificant value resembling the coefficient in column (4). In the last column, which combines quartiles of Low and Medium competition, we observe results similar to those in column (2) in Table 3, suggesting that on average, a 1% increase in the share of immigrants will increase native wages by 1%. This aligns with the findings of Ottaviano and Peri (2012), who found that the average wage of U.S.-born workers experienced a significant increase (1.8%) as a consequence of immigration. This finding is likely to be considered an interesting result as it indicates that the results obtained in the previous section are not due to the endogeneity of occupational choice but rather reflect a reliable stratification group where workers complement each other.

Following Card (2001), Dustmann et al. (2008) and Monras (2020), we attempt to segment workers into low-skilled and highly skilled natives and estimate the impact of immigrants separately for each group. To this end, we use occupation-experience stratification to estimate model (2) by categorizing native workers into groups: less-skilled workers who are in occupation groups 1 and 2; and highly skilled native workers who are in occupation groups 3 and 4. We solely focus on the effect of immigrants on specific groups, either less-skilled workers or highly skilled workers.

As shown in Table 8, the share of immigrants is associated with a negative impact of 0.24% on native wages among workers in less-skilled occupations although this effect lacks statistical significance. This finding aligns with the results observed in Table 7, columns (4) and (5), as well as Table 3, column (1). Conversely, the analysis conducted for highly skilled native workers demonstrates a positive and significant outcome. Specifically, on average, a 1% increase in the share of immigrants will increase native wages by 0.74%, which is in line with findings in Table 7, columns (1), (2), and (6), and Table 3, column (2).

[Table 8 near here]

These results, combined with the findings of Table 7, highlight several key points. Immigrants have no adverse effect on the wages of natives who are least similar to immigrants, which is consistent with findings reported by Sharpe and Bollinger (2020). However, the positive effect may diminish or even turn negative as the similarity between natives and immigrants increases, leading to competition in the labor market, particularly among less educated workers. This is in line with Borjas (2003), who asserts that the impact of immigrants is primarily concentrated among less educated natives. Specifically, he found that U.S. workers lost, on average, about 3% of the real value of their wages due to immigration over the period 1980–2000, with this loss reaching almost 9% for native workers without a high school degree. In conclusion, these findings may help explain the mixed results found in the literature. Without distinguishing among different skill groups and without estimating separately for less skilled and high skilled workers, and without considering competition quartiles that illustrate the similarity among workers, the results would reflect the sample average.

6. Conclusion

The surge in the immigration phenomenon is a notable trend that continues to gain momentum globally. The question of whether immigrants pose a threat or an advantage to labor markets remains open for debate. Many studies have examined the impact of immigrants on labor markets, yet consensus remains elusive. In contrast to prior literature centered on large countries, this paper analyzes the impacts of immigrant labor on the local labor market within a small, open economy, in

Portugal. Utilizing a comprehensive employer-employee linked dataset covering 2010 to 2019, our study focuses on occupation-experience groups (using the O*NET skill taxonomy), rather than the more conventional education-experience categories. The former has the advantage of creating more homogeneous skill groups, thus enabling us to conduct a more precise analysis of the impact of immigration on specific skill sets within occupations.

Our OLS results, in the situation where occupational cells are used, show a statistically positive impact on native wages. Specifically, our estimations illustrate that, on average, a 1% increase in the share of immigrants within an occupation-experience group is associated with a 0.357% increase in native wages. This finding underscores the complementary relationship between immigrants and natives within the same occupational and experience categories, contributing valuable insights to the existing literature on the economic impacts of immigration. While much of the prior research has documented the potential negative effects of immigration on native wages, our study provides evidence that, within specific occupational contexts, immigrants can have a beneficial effect on the wage levels of native workers. This result is also confirmed in our 2SLS estimation, which addresses potential endogeneity issues. The estimated elasticity in the 2SLS model is larger in magnitude compared to the results of OLS. This suggests that attenuation bias, potentially caused by measurement errors, significantly influences the estimates, leading to a downward bias in the OLS estimation relative to the IV estimator. Specifically, the 2SLS estimate indicates that, on average, a 1% increase in the share of immigrants within an occupation-experience group results in a 0.629% increase in native wages. The significant positive effect identified through the 2SLS approach underscores the complementary nature of immigrants in the labor market.

To ensure further robustness of the occupation stratification, we defined sextiles, deciles, and ventiles based on the communicative-to-manual skill ratio. In this case, we find positive but statistically insignificant elasticities, which are lower in magnitude compared to those reported in Table 3. This suggests that the relationship between immigrant presence and native wages might be more evident and pronounced when occupations are broadly categorized into quartiles based on their skill ratios. In finer categorizations, the variation in skill composition within each group may dilute the observed impact on native wages, potentially leading to statistically insignificant results.

Furthermore, our analysis in Section 5.1 provides a targeted exploration of the effects of immigration on the wages of demographically comparable native workers within education-experience groups. This was motivated by two primary objectives: firstly, to shed light on the contradictory results found in the main estimation Table 3 between education-experience groups and occupation-experience groups; and secondly, to explore the extent of similarities between immigrants and natives and the resulting effects on native wages. The analysis was structured around competition quartiles within the framework of education and experience. The findings of this assessment reveal that immigrants have a positive impact on native wages among those who least resemble them, while there is a shadow of a negative effect among natives who closely resemble immigrants, and competition between them is intense.

Additionally, when distinguishing between low-skilled and highly skilled natives, the analysis reveals two key findings. Among workers in less-skilled occupations, the share of immigrants is associated with a slight negative impact of 0.24% on native wages, though this effect is not statistically significant. In contrast, for highly skilled native workers, the analysis shows a positive and significant impact. Specifically, a 1% increase in the immigrant share is associated with a 0.74% increase in native wages on average, which supports the findings from the main analyses. These combined results underscore the importance of categorizing workers based on skill groups, as failure to do so may lead to estimation outcomes that reflect only a sample average. This likely contributes to the varied findings observed in the existing literature. It emphasizes the necessity of carefully selecting an approach that accurately reflects the labor market dynamics in which immigrants and natives compete with each other when assessing the wage impacts of immigrant inflows.

The use of job characteristics derived from the O*NET skill taxonomy, while providing comprehensive information, may introduce inaccuracies when applied to the Portuguese context. O*NET is designed for the United States labor market and may not fully capture the specific nuances and skill requirements of occupations in Portugal. This limitation could affect the precision of our analysis in assessing the impact of immigrant labor on native wages, particularly in terms of skill composition within occupations. The positive impact of immigrants on native wages suggests that policymakers should consider the complementary role of immigrants when formulating labor market policies and focus on improving strategies that promote integration and skill utilization among the immigrant population to maximize their potential contributions. Our findings indicate the need for future research to focus on specific economic sectors or industries to better understand how immigrant labor affects native wages across different sectors. Furthermore, comparative analyses across various countries would offer valuable insights. Finally, case studies focusing on specific nationalities in particular regions or within specific occupations, such as academic fields, could offer nuanced perspectives on how immigration influences native wages.

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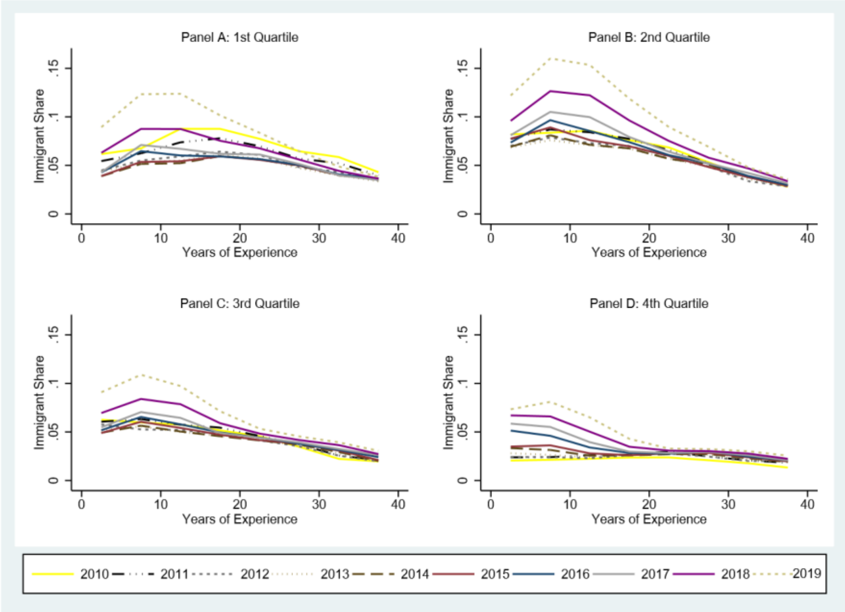
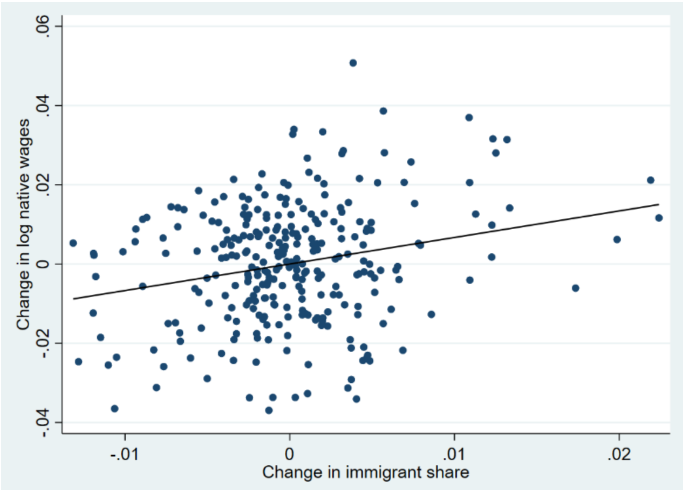
Figure 1. The share of immigrants and years of experience by quartile, 2010-2019



Notes: Each panel in this graph displays the average proportion of foreign-born employees as a share of all employees in the firm within the corresponding quartile of the communicative to manual skill task ratio.
Sources: QP, 2010-2019, and O*NET.

Figure 2. Correlation between the immigrant share and native wages, 2010-2019



Notes: The professional classification used in this analysis is based on occupation-experience groups. The change in the log native wage and the immigrant share depicted in the graph is adjusted for fixed effects of years, occupation group, and potential experience group. The coefficient of the regression line is 0.393, with a standard error of 0.148.
Source: QP, 2010-2019.

Table 1. Descriptive statistics

Worker level variables	Natives		Non-Natives	
Share (percentage of all employees)	94.43		5.57	
	men	women	men	women
Average real monthly wage	Mean (S.d.)	Mean (S.d.)	Mean (S.d.)	Mean (S.d.)
	1039.40 (864.60)	830.27 (622.05)	828.00 (905.93)	632.08 (524.30)
Age	39.21	39.10	36.79	37.13
Gender	53.98	46.02	55.22	44.78
Education				
<=4 years of schooling	10.85	10.42	13.58	17.66
5-9 years of schooling	46.39	36.74	48.47	41.13
Secondary education	26.17	28.42	28.11	28.53
Tertiary education	16.59	24.42	9.83	12.69
Tenure				
1-5 years	7.75	8.83	8.91	9.15
6-10 years	11.89	12.71	16.19	15.23
11-15 years	14.24	14.51	17.55	16.18
16-20 years	15.57	15.38	17.16	16.49
21-25 years	15.14	14.76	14.96	15.17
26-30 years	13.66	13.38	11.62	12.59
31-35 years	12.06	11.64	8.27	9.27
36-40 years	9.69	8.79	5.34	5.93
Observations (worker-year)	9,661,967	8,618,746	550,122	455,582
Total (worker-year)		19,286,417		
Year	Share of immigrants out of total employment			
2010			5.63	5.5
2011			5.20	5.2
2012			4.54	4.8
2013			4.42	4.6
2014			4.45	4.5
2015			4.59	4.4
2016			4.88	4.6
2017			5.18	4.8
2018			6.10	5.4
2019			7.55	6.5

Notes: The wage variable underwent winsorization at the 1st and 99th percentiles. The share of immigrants and the employment of natives are presented in percentage.
Sources: QP, 2010-2019.

Table 2. Coefficient Estimates for $-\frac{1}{\sigma_n}$

Model	Educ-Exp groups (1)	Educ-Exp groups (2)	Educ-Exp groups (3)	Educ-Exp groups (4)	Occ-Exp groups (5)	Occ-Exp groups (6)	Occ-Exp groups (7)	Occ-Exp groups (8)
(1) Male workers, OP	0.035 (0.022) [0.032]	0.035 (0.023) [0.058]	-0.146*** (0.024) [0.940]	-0.118** (0.046) [0.963]	-0.099** (0.038) [0.147]	-0.111** (0.042) [0.169]	-0.067** (0.025) [0.919]	-0.108*** (0.036) [0.958]
(2) Male workers, correct weighting	0.057*** (0.015) [0.102]	0.061*** (0.016) [0.137]	-0.133*** (0.024) [0.944]	-0.036 (0.044) [0.974]	-0.051* (0.027) [0.048]	-0.054 (0.035) [0.055]	-0.029 (0.035) [0.872]	-0.125** (0.046) [0.964]
(3) Male and female workers, OP	0.048* (0.024) [0.068]	0.045* (0.025) [0.119]	-0.114*** (0.029) [0.93]	-0.146*** (0.046) [0.962]	-0.121*** (0.020) [0.352]	-0.133*** (0.021) [0.403]	-0.075** (0.027) [0.898]	-0.093*** (0.026) [0.966]
(4) Male and female workers, correct weighting	0.057** (0.021) [0.097]	0.053** (0.023) [0.145]	-0.116*** (0.026) [0.939]	-0.091** (0.042) [0.972]	-0.094*** (0.019) [0.209]	-0.110*** (0.022) [0.259]	-0.062* (0.032) [0.854]	-0.108** (0.042) [0.971]
(5) Full time only, OP	0.032 (0.021) [0.028]	0.034 (0.022) [0.053]	-0.158*** (0.027) [0.929]	-0.092* (0.047) [0.956]	-0.102*** (0.037) [0.172]	-0.110** (0.040) [0.187]	-0.077*** (0.026) [0.916]	-0.073** (0.030) [0.956]
(6) Full time only, correct weighting	0.050*** (0.014) [0.083]	0.057*** (0.016) [0.115]	-0.145*** (0.023) [0.939]	-0.012 (0.046) [0.974]	-0.055** (0.026) [0.057]	-0.058* (0.034) [0.064]	-0.045 (0.034) [0.881]	-0.095** (0.043) [0.962]
Year dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Education/ Occupation × experience	No	No	Yes	Yes	No	No	Yes	Yes
Education × year	No	No	No	Yes	No	No	No	Yes
Experience × year	No	No	No	Yes	No	No	No	Yes
Education/Occupation groups	4	4	4	4	4	4	4	4
Experience groups	8	8	8	8	8	8	8	8
Total skill groups	32	32	32	32	32	32	32	32
Observations	320	320	320	320	320	320	320	320

Notes: The model is given by equation (1). In all specifications, the sample is restricted to workers aged 18–65. Each cell in the table displays between immigrants and natives within a specific skill group, obtained from separate regressions. These regressions involve the log relative wages of immigrants and natives within each skill group regressed on the log relative supply of immigrant and native labor, along with skill group dummies and year dummies. Columns differ according to the definition of the skill group: education-experience (columns 1 to 4), and occupation-experience (columns 5 to 8). Rows vary based on the sample used for constructing the dependent variable: all male workers with OP weight (row 1), all male workers with the inverse of the sampling variance of the dependent variable (row 2), male and female workers combined with OP weight (row 3), male and female workers combined with the inverse of the sampling variance of the dependent variable (row 4), only full-time male workers with OP weight (row 5), and only full-time male workers with the inverse of the sampling variance of the dependent variable (row 6). Robust standard errors are reported in parentheses and are clustered by education–experience/occupation–experience cells. Adjusted R-squared is reported in brackets. ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 3. The Impact of the immigrant share on native wages, 2010–2019

Model	Educ-Exp Groups (1)	Occ-Exp Groups (2)
(1) Basic estimates weighted	-1.114*** (0.326) [-0.512]	0.776* (0.403) [0.357]
(2) Basic estimates unweighted	-0.635*** (0.220) [-0.292]	1.353*** (0.416) [0.622]
(3) Includes log native labor force	-1.299*** (0.309) [-0.597]	0.728* (0.409) [0.335]
(4) Residualized log wages	0.293 (0.187) [0.135]	0.701*** (0.223) [0.322]
(5) Male and female workers	-1.689*** (0.409) [-0.827]	0.934*** (0.346) [0.458]
(6) 2SLS	No	1.368*** (0.427) [0.629]
(7) 2SLS with native labor force	No	0.728*** (0.266) [0.335]
Year dummies	Yes	Yes
Education/Occupation groups	4	4
Experience groups	8	8
Total skill groups	32	32
Resulting observations	320	320

Notes: The elasticity is reported in square brackets, while the underlying estimated coefficient is given by the first value at the top of each cell, using the model in equation (2). In all specifications, the sample is restricted to native male workers aged 18–65 with 1–40 years of potential experience, unless otherwise noted. The dependent variable is the average log wages in all rows except row (4), where it is the mean of the residualized log wages. All regressions are weighted by the sample size of the education-experience group (column 1) or the occupation-experience group (column 2), except row (2), which is unweighted. The regressions control for occupation/education, experience, and period fixed effects. Additionally, interactions between occupation/education and experience fixed effects, occupation and period fixed effects, and experience and period fixed effects are included to account for various sources of variation. In row (3), the estimates include native labor supply as a control variable, while in row (5) the sample is expanded to include both male and female workers, addressing potential gender differences in labor market outcomes. Ordinary Least Squares (OLS) estimation with robust standard errors is used in columns (1) and (2). However, in column (2), rows (6) and (7), we employ a two-stage least squares (2SLS) approach using the *ivreg2* command in Stata to address the potential endogeneity of the immigrant share. The instrumented variable in these rows is the share of immigrants. In row (7), we further include the native labor force as a regressor in the 2SLS estimation. ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively; standard errors are given in parentheses and the estimated elasticity is reported in square brackets.

Table 4. First stage results of the 2SLS implementation in Table 3

	Model	
	Table 3, column (2) Row 6	Table 3, column (2) Row 7
	(1)	(2)
	Immigrant share	Immigrant share
Instrumental variable	-0.014*** (0.002)	-.0216*** (0.002)
Number of observations	320	320
F-stat of first stage	27***	61***
F-stat (Sanderson-Windmeijer multivariate)	27***	61***
Underidentification test: (Kleibergen-Paap rank LM statistic) Chi-sq(1)	27 ***	44***
Weak identification test: F-stat of Cragg-Donald Wald	26	67
F-stat of Kleibergen-Paap rank Wald (10% maximal IV size):	Critical value: 16.38 27	Critical value: 16.38 61
Overidentification test: Joint of Hansen statistic	0.000	0.000

Notes: In each column, the dependent variable is given by the endogenous variable, immigrant share. The set of fixed effects and interaction terms is the same as in Table 3. Under identification test (Kleibergen-Paap rank LM statistic): Null Hypothesis: The instrument is weak and irrelevant in explaining the endogenous variables. Weak identification test (Cragg-Donald Wald): Null Hypothesis: The instrument is weak and does not adequately predict the endogenous variables. Over identification test (Hansen J statistic): Null Hypothesis: The instrument is uncorrelated with the error term and does not suffer from over identification bias. ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively; standard errors are given in parentheses.

Table 5. Impact of the immigrant share on native wages, alternative occupation classifications 2010–2019

	Occupation-Experience Groups (1) w_{ijt}	Occupation-Experience Groups (2) $\tilde{w_{ijt}}$
(1) Occupation groups 6 Observations : 480	0.240 (0.236) [0.110]	0.301* (0.155) [0.138]
(2) Occupation groups 10 Observations : 800	0.106 (0.161) [0.049]	0.169 (0.104) [0.077]
(3) Occupation groups 20 Observations : 1,600	0.048 (0.111) [0.022]	0.048 (0.083) [0.022]
Year dummies	Yes	Yes
Experience groups	Yes	Yes

Notes: The table uses model (2) and presents the coefficient estimate of the immigrant share variable across various groups, with the estimated elasticity is reported in square brackets. The sample is limited to native males aged 18–65 with 1–40 years of potential experience. In column (1) the dependent variable is the average log wages. In column (2), the dependent variable is the mean of the residualzed log wage. All regressions are weighted by sample size and control for occupation, experience, and period fixed effects. Additionally, interactions between occupation and experience fixed effects, occupation and period fixed effects, and experience and period fixed effects are included. Row (1) shows estimates for a 6-group classification, row (2) for a 10-group classification, and row (3) for a 20-group classification. Both columns (1) and (2) use an OLS estimator with robust standard errors. ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively; standard errors are given in parentheses.

Table 6. Mean characteristics of native workers by intensity of competition level with immigrants, 2016

Variable	Low competition	Medium competition	High competition	Very high competition
Wage	1160.26	967.34	1122.41	849.10
Experience	26.50	21.49	21.65	15.98
Living in Lisboa	4.63%	10.27%	47.33%	74.31%
Fulltime	82.88%	89.25%	90.34%	90.97%
<=4 years of education	18.50%	5.06%	7.95%	6.20%
5-9 years of education	29.13%	38.62%	56.30%	59.94%
Secondary education	13.53%	44.45%	18.47%	31.63%
Tertiary education	38.83%	11.86%	17.28%	2.23%
Occupation group 1	28.03%	42.98%	40.30%	39.84%
Occupation group 2	13.78%	20.64%	18.99%	28.07%
Occupation group 3	16.79%	17.17%	16.31%	20.36%
Occupation group 4	41.39%	19.20%	24.40%	11.73%
Observations	292,041	292,045	291,996	292,009

Note: Summary statistics (means) derived from the 2016 wage sample for male native workers. Low competition quartile: Foreign-born workers in this quartile have the lowest predicted probabilities of being native. Medium competition quartile: This quartile represents moderate level of predicted probabilities. Foreign-born workers in this quartile are more evenly distributed in terms of their predicted probabilities. High competition quartile: Foreign-born workers in this quartile have the highest predicted probabilities of being native. They are more likely to be categorized as native compared to those in low and medium quartiles. Very high competition: This quartile includes foreign-born workers with the very highest predicted probabilities of being native. They are significantly more likely to be categorized as native compared to those in other quartiles.

Table 7. Impact of immigrant share on native wages by competition intensity

Variables	Low competition (1)	Medium competition (2)	High competition (3)	Very high competition (4)	Top (High and Very High) (5)	Bottom (Low and Medium) (6)
Immigrants share (s_{ijt})	3.330* (1.768) [1.532]	4.581*** (1.653) [2.107]	0.890 (1.407) [0.409]	-0.715 (0.926) [-0.329]	-0.595 (0.459) [-0.274]	2.244*** (0.717) [1.032]
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Education groups	4	4	4	4	4	4
Experience groups	8	8	8	8	8	8
Total skill groups	32	32	32	32	32	32

Notes: The table uses model (2) and presents the coefficient estimate of the immigrant share variable across various groups, with the estimated elasticity reported in square brackets. The sample is limited to native males aged 18-65 with 1-40 years of potential experience. The dependent variable is given by the average log wages in the corresponding competition intensity case. All regressions are weighted by the sample size and control for education, experience, and period fixed effects. Additionally, interactions between education and experience fixed effects, education and period fixed effects, and experience and period fixed effects are included. We use the OLS estimator with robust standard errors. ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively; standard errors are given in parentheses.

Table 8. Impact of immigrant share on native wages, by skill composition, 2010–2019.

	Low-Skilled (1)	Highly Skilled (2)
Immigrants share (s_{ijt})	-0.520 (0.326) [-0.239]	1.612*** (0.293) [0.741]
Year dummies	Yes	Yes
Occupation groups	4	4
Experience groups	8	8
Total skill groups	32	32
Observations	160	160

Notes: The table displays the impact of immigrants on native wages, segmented by the skill level of native workers. It categorizes native workers into less-skilled (occupation groups 1 and 2) and highly skilled (occupation groups 3 and 4) groups, with the estimated elasticity reported in square brackets. The sample is limited to native males aged 18–65 with 1–40 years of potential experience. All regressions are weighted by the sample size and control for occupation, experience, and period fixed effects. Interactions between occupation and experience fixed effects, occupation and period fixed effects, and experience and period fixed effects are included. We use the OLS estimator with robust standard errors in both columns (1) and (2). ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively; standard errors are given in parentheses.

Appendix

Appendix Table A. 1 — Distribution of the foreign-born male work force across education and experience levels, 2010–2019

Education	Years of experience	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
<=4 years of schooling	1-5	5.25	4.632	4.43	4.36	3.81	4.25	4.80	4.34	5.43	6.90
	6-10	10.21	11.44	10.67	10.73	10.91	10.68	12.54	11.83	12.16	14.28
	11-15	15.17	14.57	14.40	13.53	13.13	13.86	14.59	14.21	15.13	15.96
	16-20	17.91	18.35	17.36	16.76	16.20	16.73	15.24	14.88	15.17	16.09
	21-25	17.03	16.51	16.36	16.54	16.60	16.22	15.67	16.44	15.68	14.30
	26-30	14.80	14.22	15.20	15.74	16.06	15.10	13.96	14.36	13.57	13.18
	31-35	11.98	12.12	12.29	12.73	13.25	13.36	13.20	13.26	12.63	10.47
	36-40	7.644	8.15	9.27	9.61	10.04	9.79	10.00	10.66	10.21	8.82
5-9 years of schooling	1-5	8.03	7.027	6.33	6.02	5.95	6.11	6.37	6.92	7.86	8.28
	6-10	14.24	14.01	13.76	13.51	13.31	13.67	14.59	15.20	15.52	16.72
	11-15	18.96	17.99	17.08	16.76	16.04	16.16	16.59	17.40	17.75	18.57
	16-20	19.46	19.48	19.47	18.87	17.87	17.06	16.53	16.07	16.51	17.04
	21-25	15.85	16.38	17.02	17.37	17.02	17.02	16.37	16.10	14.96	14.35
	26-30	11.40	12.02	12.39	12.86	13.94	13.89	13.44	12.78	12.39	11.58
	31-35	8.00	8.51	8.78	8.98	9.60	9.55	9.48	9.25	9.03	8.13
	36-40	4.05	4.59	5.15	5.61	6.27	6.53	6.62	6.264	5.97	5.33
Secondary education	1-5	11.04	10.17	9.63	9.78	10.74	11.57	12.08	12.83	13.70	14.29
	6-10	17.88	17.00	15.84	15.57	16.23	17.10	18.29	19.42	20.29	21.70
	11-15	21.84	20.16	19.46	18.52	17.46	16.51	16.72	17.23	18.33	19.38
	16-20	18.83	18.90	18.86	18.81	18.32	17.55	16.49	15.52	15.39	15.51
	21-25	12.89	13.96	14.96	14.87	14.87	14.83	14.07	13.40	12.95	11.92
	26-30	9.23	10.00	10.49	10.92	10.98	10.51	10.70	10.36	9.14	8.45
	31-35	5.72	6.36	6.74	7.39	7.30	7.35	7.09	6.80	6.23	5.23
	36-40	2.56	3.43	4.02	4.12	4.09	4.54	4.54	4.43	3.98	3.51
Tertiary education	1-5	8.56	7.33	7.02	7.39	8.09	8.47	10.84	11.51	13.11	14.08
	6-10	16.96	14.77	13.59	13.04	13.04	13.38	15.15	16.94	18.79	20.61
	11-15	21.91	20.27	17.97	16.98	16.52	15.58	14.71	15.61	16.72	18.89
	16-20	18.07	18.19	20.02	19.46	18.55	18.05	17.55	16.07	15.53	14.85
	21-25	14.13	15.54	15.91	16.55	16.47	16.55	15.21	14.82	13.53	12.08
	26-30	9.83	11.66	12.22	13.04	13.00	13.01	12.50	11.25	10.23	9.12
	31-35	6.51	7.19	7.85	8.24	8.80	9.46	8.91	8.72	7.70	6.46
	36-40	4.01	5.04	5.24	5.30	5.53	5.49	5.12	5.08	4.38	3.90

Notes: The table displays the percentage of the foreign-born labor force categorized by education group and experience group separately for each year.
Source: QP, 2010-2019.

Appendix Table A. 2—O*NET elements (by domain) used in task intensity indices

Abilities	Task Category
Oral Comprehension	Communicative
Oral Expression	Communicative
Written Comprehension	Communicative
Written Expression	Communicative
Fluency of Ideas	Communicative
Originality	Communicative
Inductive Reasoning	Communicative
Deductive Reasoning	Communicative
Perceptual Speed	Communicative
Speech Clarity	Communicative
Speech Recognition	Communicative
Speed of Limb Movement	Manual
Arm-Hand Steadiness	Manual
Response Orientation	Manual
Finger Dexterity	Manual
Multi-limb Coordination	Manual
Reaction Time	Manual
Wrist-Finger Speed	Manual
Rate Control	Manual
Control Precision	Manual
Manual Dexterity	Manual
Gross Body Coordination	Manual
Trunk Strength	Manual
Extent Flexibility	Manual
Static Strength	Manual
Dynamic Strength	Manual
Dynamic Flexibility	Manual
Stamina	Manual
Gross Body Equilibrium	Manual
Explosive Strength	Manual
Knowledge	
English Language	Communicative
Communications	Communicative
Building and Construction	Manual
Mechanical	Manual
Skills	
Reading Comprehension	Communicative
Active Listening	Communicative
Writing	Communicative
Speaking	Communicative
Installation	Manual
Operation Monitoring	Manual
Equipment Maintenance	Manual
Work Activities	
Interpreting the Meaning of Information for Others	Communicative
Communicating with Supervisors, Peers, or Subordinates	Communicative
Communicating with Persons Outside Organization	Communicative
Establishing and Maintaining Interpersonal Relationships	Communicative
Assisting and Caring for Others	Communicative

Selling or Influencing Others	Communicative
Resolving Conflicts and Negotiating with Others	Communicative
Performing for or Working Directly with the Public	Communicative
Performing General Physical Activities	Manual
Handling and Moving Objects	Manual
Controlling Machines and Processes	Manual
Operating Vehicles, Mechanized Devices, or Equipment	Manual

Note: Source O*NET Content Model, 2018.

Appendix Table A. 3 —Variable definition and estimation sample means

Variable	Definition	Mean
Male wage	Mean monthly wages for native male workers. (In logs). Following Cardoso and Portela (2009), gross monthly earnings were derived by adding the base wage (gross pay for normal hours of work), seniority-indexed components of pay, and other regularly paid components. To account for inflation, wages were adjusted using the consumer price index.	1039.40
Both male female wage	Mean monthly wages for both native male and female workers. (In logs.)	934.83
Share of immigrants	Share of immigrants in the firm's workforce. It is defined as a proportion of foreigners in total employment in the firm. (In percentage.)	5.57
Education group (4 groups):		
Workers share with 4 years or less of formal education	Share of native workers with 4 or less years of formal education as a proportion of total employment in the firm. (In percentage.)	10.85
Workers share with 5–9 years of formal education	Share of native workers with 5–9 years of education as a proportion of total employment in the firm. (In percentage.)	46.39
Workers share with secondary education	Share of native workers with secondary education as a proportion of total employment in the firm. (In percentage.)	26.17
Workers share with tertiary education	Share of native workers with tertiary degrees as a proportion of total employment in the firm. (In percentage.)	16.59
Potential labor market experience	It is given by (age - 6 - schooling years).	
Experience groups (8 groups):		
Experience group 1	Native workers who have 1-5 years of potential experience.	7.75
Experience group 2	Native workers who have 6-10 years of potential experience.	11.89
Experience group 3	Native workers who have 11-15 years of potential experience.	14.24
Experience group 4	Native workers who have 16-20 years of potential experience.	15.57
Experience group 5	Native workers who have 21-25 years of potential experience.	15.14
Experience group 6	Native workers who have 26-30 years of potential experience.	13.66
Experience group 7	Native workers who have 30-35 years of potential experience.	12.06
Experience group 8	Native workers who have 36-40 years of potential experience.	9.69
Occupation groups (4 groups):	The skill ratios is calculated as the ratio of communicative task intensity to manual task intensity ($\frac{\mathrm{TS}_j^{\mathrm{comm}}}{\mathrm{TS}_j^{\mathrm{manual}}}$). These skill ratios define the occupational groups based on their relative task intensities in four occupational groups.	
Occupation group 1	These jobs are primarily blue-collar manual-labor occupations with the lowest communicative-to-manual task intensity, meaning they require minimal communication and focus heavily on manual tasks. Examples include jobs like assembly line workers, construction laborers, and maintenance workers.	40.70
Occupation group 2	These jobs still involve significant manual labor but require more communication compared to those in occupation group 1. They require a moderate communicative-to-manual task intensity, balancing physical tasks with some communicative responsibilities. Examples include jobs like machine operators, skilled trade workers (electricians, plumbers), and some logistics roles.	21.27
Occupation group 3	These roles involve a more balanced mix of manual tasks and communicative responsibilities. They require a higher communicative-to-manual task intensity, with a significant portion of tasks requiring communication and coordination. Examples include positions such as supervisors of manual workers, customer service roles in technical fields, and technical support roles.	17.27
Occupation group 4	These jobs demand the highest level of both communication and manual task intensity and are often found in professional or white-collar settings. They require very high communicative-to-manual task intensity, where communication and interpersonal skills are essential. Examples include	20.77

	roles such as managers, consultants, educators, and healthcare professionals.	

Notes: To avoid the influence of extreme values, earnings below the 1st percentile and above the 99th percentile are excluded from the analysis.
Sources: QP, 2010-2019, and O*NET.