From Borders to Boardrooms: Immigrants' Impact on Productivity

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Abstract

In this study, we investigate the impact of the share of the foreign labor force on the labor productivity of firms operating in Portugal between 2010 and 2019, drawing on data from two main sources: linked employer-employee data from Quadros de Pessoal and firm-level balance sheet data from SCIE-Sistema de Contas Integradas das Empresas. The empirical analysis, conducted using Fixed Effects Two-Stage Least Squares, shows that immigrants do not contribute to the productivity of firms in which they are employed. We further investigate whether the productivity response to increased immigrant labor varies across different subsamples. Notably, low-productivity firms experience adverse effects when the share of immigrants rises, whereas smaller firms benefit from their presence. Furthermore, our analysis shows a positive and statistically significant impact on labor productivity from foreign-born workers with 5 to 9 years of formal education. This finding suggests that this particular demographic brings valuable skills and contributions to the workforce, enhancing overall productivity levels.

Keywords: Firms, Immigration, Low skilled Immigrants, Productivity.

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1. Introduction

Migration defines our interconnected world, transcending borders and sparking debates on immigrant integration. The global discourse questions whether newcomers can seamlessly adapt to their host societies or remain perceived as foreign entities. Despite resistance, immigrants consistently prove to be catalysts for change, contributing significantly to the economic, cultural, and social fabric of their adopted nations. In addition to enriching the cultural tapestry of host nations, migration is also a powerful driver of economic growth. Research by Ortega and Peri (2009) highlighted how immigration has the potential to boost per capita income, accumulate physical capital, and enhance overall productivity in destination countries. Businesses benefit from this increased productivity (Ottaviano et al., 2010), and immigrants, alongside specialized native workers, improve production efficiency through complementary tasks (Peri and Sparber, 2009). Highly skilled immigrants are also crucial for fostering innovation and local productivity growth (Kerr and Lincoln, 2010; Peri et al., 2015), further propelling productivity (Peri, 2012; Bahar and Rapport, 2018). However, the introduction of foreign workers may lead to potential negative consequences, such as labor market crowding, which may disadvantage native workers (Mitaritonna et al., 2017).

Does an increase in a foreign labor force constitute a factor in the productivity of firms? The primary aim of this paper is to empirically explore this question within the framework of Portuguese firms from 2010 to 2019. Various scenarios emerge from this investigation. Immigrants often bridge labor gaps in industries and sectors experiencing shortages of qualified workers, a significant issue in Portugal due to the progressive aging of society and the labor force. This demographic shift has led to labor shortages across various sectors, making the presence of young migrants during this period potentially beneficial for the country's microeconomic performance.

Furthermore, the study period witnessed a rising trend in young and educated immigrants, coupled with a decline in less educated immigrants. The proportion of highly skilled immigrants among the top 10 occupations experienced a notable increase of 1.4 percentage points over this timeframe, indicating a shift from the past. This trend suggests that the new group of immigrants, which has the potential to alleviate shortages in the domestic labor market, may bring higher levels of education and skills to the workforce and consequently could potentially enhance productivity levels across various sectors of the economy. However, the presence of foreign labor can trigger crowding effects, leading to increased job competition, lower wages, higher turnover rates, skill mismatches, and a stressful work environment, all of which negatively impact firm productivity.

In the domain of literature concerning immigration, many studies analyze migration patterns using aggregate data, correlating immigrant shares in countries or regions with overall productivity levels. However, this approach requires strong identification assumptions and is prone to omitted-variable bias, as illustrated by Ortega and Peri (2014), Mitaritonna et al. (2017), and Fassio et al. (2020). Unlike these studies, which adopt a *geographical* approach and use regions as their unit of analysis, our research focuses on the link between migration and productivity at the *firm level*. This approach helps mitigate bias by incorporating firm-specific characteristics and firm fixed effects, allowing for a more precise evaluation of how immigration influences productivity and offering a clearer understanding of this connection.

Given the distinct characteristics of small firms, which often exhibit greater flexibility in their labor market practices, and the characteristics of less productive firms, which typically rely more on low-skilled labor, our paper examines whether the productivity impact of an increase in immigrant labor supply differs across the two selected firm performance dimensions.

The analysis reveals a number of interesting results. Firstly, there is no association between the share of immigrants and labor productivity (LP). However, a potential limitation in our study arises from the non-random distribution of immigrants among firms. To address this issue, in Section 4, we tackle the potential endogeneity of migrants by utilizing a shift-share instrument, a method derived from the framework outlined by Card (2001). Notably, there is confirmation that the share of immigrants does not affect LP. However, by categorizing firms based on both productivity levels and size, a notable finding emerges: firms operating below the median productivity level exhibit a significant negative coefficient of -1.307, while, conversely, firms operating below the employment level have a positive impact of immigrant presence in the coefficients of the explanatory variable in the 2SLS estimation. The negative coefficient observed in less productive firms suggests potential challenges in integrating immigrant labor effectively. In contrast, the positive impact in firms with lower employment levels suggests that immigrants may contribute positively to productivity dynamics under certain conditions.

The remaining sections of the paper are structured as follows: In the subsequent section, a comprehensive review of existing literature regarding the influence of immigrants on firm’s productivity is presented. Section 3 provides a detailed description of the data utilized in the study. Section 4 introduces the econometric approach employed in the analysis, along with the robustness test 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 conclude the paper, summarizing the key findings and implications derived from the research.

2. Literature review

In the migration literature, the influence of immigrants has been subject to extensive study. This persistent attention from scholars is driven by the enduring relevance and evolving nature of migration dynamics, which continue to shape societies worldwide. Moreover, as we progress further into the 21st century, the ongoing growth of migration is marked by contemporary challenges and complexities. The current global landscape, characterized by rapid globalization, shifting demographic trends, economic disparities, and geopolitical tensions, underscores the need for policymakers to reevaluate and recalibrate their approaches towards immigration and related issues.

Several seminal studies have examined the impact of immigration on various aspects of the economy. Friedberg and Hunt (1995) found minimal negative effects on native workers' wages. Similarly, Dustmann et al. (2005) and Ma (2020) identified some negative impacts on individuals with intermediate education levels and highly skilled native-born workers, respectively. Adverse wage effects are exemplified by Aydemir and Borjas (2007), Borjas (2015), and Malchow-Møller et al. (2012). Card (2001 and 2005) extended these findings by identifying modest wage reductions among specific native-born groups and limited adverse effects on less educated native workers.

Borjas (2006) highlighted reduced earnings for both native and foreign workers in similar fields influenced by foreign-born doctorates. In contrast, Lewis (2011) demonstrated that manufacturing automation, complemented by immigration, mitigates its wage impact.

When investigating the impact of immigrants on output and economic growth, Dolado et al. (1994) integrated migrant workers into a Solow growth model, demonstrating that immigrants with higher human capital can mitigate detrimental effects on economic growth compared to native-born individuals. Kangasniemi et al. (2012) contrasted the UK's relatively minor negative effect on productivity due to immigration with Spain's more significant negative impact. Additionally, Hiller (2013) illustrated that immigration in Denmark enhances firm-level exports, particularly in small firms. Moreover, Ortega and Peri (2012) analyzed international migration determinants, focusing on policy and income effects. Ortega and Peri (2014) and Peri (2012) highlighted immigration's positive impacts on productivity and income through diversity and productivity growth, respectively. Likewise, Kerr and Lincoln (2010) and Alesina et al. (2016) explored immigration's role in fostering innovation and economic development, revealing positive outcomes in technology and prosperity. Similarly, Bosetti et al. (2015) found significant contributions to local innovation and knowledge creation in Britain and Europe, while Hatzigeorgiou and Lodefalk (2016) identified the positive impacts of foreign-born workers on firm performance in Sweden. On the other hand, Quispe-Agnoli and Zavodny (2002) observed slower productivity growth in sectors with a higher immigrant presence.

Mitaritonna et al. (2017) found a positive association between an increase in local immigrants and higher total factor productivity among French manufacturing firms, especially smaller and less productive ones, leading to increased capital growth, expanded exports, and higher native wages. Ottaviano et al. (2018) highlighted immigrants' contributions to productivity in UK service-producing firms through cost-cutting effects and reducing country-specific offshoring activities, thereby enhancing service exports. Examining labor market dynamics, Clemens et al. (2018) concluded that the exclusion of Mexican bracero workers from the US had minimal impact on overall labor market outcomes, challenging assumptions about the dependence of technological advancements on immigrant labor. Furthermore, Haaland and Roth (2020) also demonstrated that providing evidence of minimal or no adverse impacts on the labor market can increase support for immigration policies.

Karim et al. (2020) highlighted the dual role of skilled immigrants in the US labor market, acting both as substitutes and complements across various occupations. Meanwhile, Meehan et al. (2021) explored European education policies for newly arrived migrant students, revealing a blend of standardized approaches and localized adaptations. In Danish manufacturing firms, Bitzer et al. (2021) uncovered a substantial boost in productivity and innovation due to immigrant employees. Brücker et al. (2021) demonstrated that formal recognition of foreign qualifications among immigrants in Germany significantly enhances their employment prospects and wages. Additionally, Alaverdyan and Zaharieva (2022) identified a reliance on social networks among immigrant workers in Germany, influencing occupational outcomes and positively impacting the integration of second-generation immigrants into the labor market.

In addition, Lee et al. (2022) observed gender-specific labor market convergence among migrants in EU-15 countries and Switzerland, highlighting varying employment outcomes influenced by local attitudes and economic conditions. Koumenta et al. (2022) found that occupational licensing posed significant barriers to migrant workers across EU countries, contributing to wage differences. Meanwhile, Mehra and Kim (2023) stressed the importance of considering skilled immigration's impacts on offshoring and trade in the US, cautioning against overestimating benefits in policy evaluations. Pulido and Varón (2024) quantified the potential productivity gains in Colombia by reducing occupational barriers for Venezuelan immigrants, underscoring immigration's positive economic impact. In Portugal, Martins et al. (2018) revealed positive employment effects for lower-skilled natives employed in the same firms and occupations as immigrants. Conversely, Bohnet et al. (2021) analyzed the repercussions of a significant return migration event in Portugal, highlighting profound shifts in employment patterns among native populations following the repatriation of Portuguese-born individuals.

The originality of our contribution stems from the fact that it is the first, as far as we know, to explicitly assess the effect of immigrants on labor productivity among manufacturing and service firms by specifically examining the relationship with firm size and productivity level. Additionally, this study introduces a novel assessment of the impact of specific foreign-born low-skilled groups. Finally, it merges large linked employer-employee data with firm-level balance sheet information in a way that has never been used for the analysis of the of the economic effects of migration.

3. Data

3.1. Data sources

Our dataset comprises two primary sources of information. The first source is Quadros de Pessoal (QP), a linked employer-employee longitudinal dataset provided by the Ministry of Labour, Solidarity and Social Security. This dataset covers all employees in private enterprises and spans the period from 2010 to 2019. It contains comprehensive information provided by employers, including industry affiliation, the number of employees, job titles, wages, and individual characteristics such as gender, age, schooling level, and years of service (i.e. tenure).

The second source of information is based on firm-level balance sheet data, extracted from SCIE-Sistema de Contas Integradas das Empresas. The SCIE dataset contains the population of non-financial firms in the country and is compiled through a mandatory annual business survey conducted by the Portuguese Statistical Office (INE). It includes crucial information such as value-added, total sales, the value of assets in the capital stock, and the use of intermediate goods by firms. Our estimation sample is restricted to firms in the manufacturing and services sectors, excluding utilities, the financial sector, and not-for-profit sectors such as education, health care, and cultural services. Firms in this dataset are also followed longitudinally.

3.2. Descriptive statistics

During the data cleaning process, we excluded all observations with non-strictly positive values for gross output and total net assets. In addition, firms with an undefined age were excluded.

Accordingly, our final sample comprises an unbalanced panel of 549,865 firms, constituting 2,808,027 firm-year observations. Out of these, 45,866 observations are associated with firms that have both native (i.e., born in Portugal) and non-native (i.e., immigrants) workers. Regarding firm size, some 512,516 have 10 employees or fewer, another 76,487 fall within the 10–250 employee category, while only 1,639 firms exceed 250 workers.

At worker level, individuals are classified into natives and non-natives. The demographic composition reveals that immigrants constitute 5% of the total. The average age of immigrants is 37 years, highlighting a relatively young labor force. In contrast, non-immigrants are on average 40 years old.

By examining the educational distribution of workers within their own groups we observe that immigrants exhibit a slightly higher proportion of individuals with secondary education compared to native-born counterparts. Specifically, 28% of immigrants have secondary education, 26% in the case of natives. However, it is noteworthy that although the majority of both natives and immigrants fall into the 5 to 9 years education group, the proportion of tertiary education is higher among natives than among immigrants. Summary statistics of the selected variables for the variables used in our estimates for firms operating in Portugal between 2010 and 2019 are given in Table 1.

[Insert Table 1 here]

3.3. Contribution of immigrant skills to the workforce

In this section we illustrate the migration patterns in Portugal from 2010 to 2019. To this end we analyze the communicative-to-manual task intensity within different occupations carried out by workers. This analysis helps us understand the balance between communication-oriented tasks and manual tasks within various professions. (For a more comprehensive understanding of the specific professional groups and their classification, we refer to the detailed construction provided in the Appendix A.1)

Table 2 displays the changes over time in the proportion of immigrants' skills within the overall labor force. As can be seen, there was a greater increase in the immigrant share among occupations with a higher communicative-to-manual index compared to occupations with a lower level of communicative-to-manual task intensity. Specifically, among the top 10 occupations with a high index, the immigrant share increased by 1.3 percentage points (p.p.), whereas the share of foreign workers in occupations with a low level of communicative-to-manual task intensity only increased by 0.9 percentage points (p.p.). In the last two rows, workers are categorized based on collar colors, specifically blue-collar and white-collar workers. We observe a similar pattern in both groups. The share of production (blue-collar) workers has increased by 0.8 percentage points (p.p.), while the share of non-production (white-collar) workers has experienced a larger change, rising by 1.2 percentage points (p.p.).

[Insert Table 2 here]

The first criterion for evaluating the skills of immigrants can be inferred from Figure 1, which provides a visual representation of the distribution of foreign-born workers based on their educational attainment levels from 2010 to 2019. Notably, we observe a decreasing proportion of immigrants with 5 to 9 years of education or less during this period. In contrast, there has been a noticeable increase in the percentage of immigrants with secondary education or higher levels of education. This shift in educational attainment among foreign-born workers underscores the evolving skill landscape. Natives remain the predominant group, holding a larger share of the total compared to immigrants.

[Insert Figure 1 here]

In Figure 2 we look at a particular group, that is, workers with tertiary education, where we plot the natural logarithm of the number of workers with tertiary education over the years 2010 to 2019. In line with the findings in Figure 1, we observe a slight increase in the number of workers with tertiary education among non-native individuals, compared to natives. Natives remain the predominant group, holding a larger share of the total compared to immigrants. Given that non-native individuals make up a small proportion of the population, even minor changes in their absolute numbers can lead to notable shifts in their relative proportion within the entire group or population.

[Insert Figure 2 here]

Another criterion for evaluating the education composition of the workforce across natives and immigrants, this time in sectorial detail, is depicted in Figure 3, which represents the percentage of workers in each sector, categorized into four educational groups.

In Panel A, a distinct pattern emerges among native workers, showcasing a predominant presence within the wholesale and retail trade sector, followed by manufacturing. Interestingly, sectors such as construction and accommodation and food service activities exhibit an equitable distribution in terms of workforce representation. Conversely, Panel B delineates a divergent trend among immigrant workers, where the majority find employment within the wholesale and retail trade and accommodation and food service activities sectors, with construction closely trailing behind. Noteworthy is the discernible variance in education composition across sectors. In both panels, individuals with 5 to 9 years of education constitute the prevailing demographic. However, upon closer inspection, it becomes evident that certain sectors attract a higher proportion of tertiary education individuals, particularly within the information and communication and professional, scientific and technical activities sectors. This phenomenon is to be expected, given the propensity of these sectors to absorb highly educated workers, thereby necessitating a predominance of skilled labor. Appendix Table A.2. provides additional information on the distribution of workers across sectors.

[Insert Figure 3 here]

4. Methodology

In our empirical analysis, we assess the impact of the share of immigrants on the productivity of different firms, controlling for various worker and firm's characteristics. Recognizing that firms vary in terms of productivity and size, we also anticipate that the impact of the foreign workforce on firm performance may differ accordingly. Therefore, we will further classify firms based on their productivity level and size, using median productivity and employment as reference points. By employing these benchmarks, it becomes possible to evaluate how the impact of foreign labor presence varies across different firm thresholds. The baseline estimation model is based on the work of Mitaritonna et al. (2017) as follows:

$$y_{i,t} = \theta_i + \emptyset_t + \beta_1 s_{i,t}^{IM} + \beta_2 s_{i,t}^{IM} * I_i(k_i \leq k) + \beta_3 X_{i,t} + \beta_4 Educ\_tertiaty_{i,t} + \beta_5\ Educ\_secondary_{i,t} + \beta_6 Educ\_5\ to\ 9\ years_{i,t} + \beta_7 age_{i,t} + \varepsilon_{i,t} \quad [1]$$

where subscripts i and t denote firm and time (year). The outcome of interest, $y_{i,t}$, encompasses both labor productivity (LP) and Return On Assets (ROA). LP is defined as gross value added (GVA) per worker, calculated as the difference between gross output and material inputs. To adjust for inflation, gross value added is deflated using industry-specific deflators at the 2-digit level, obtained from the INE (Instituto Nacional de Estatística). ROA is calculated as EBITDA (earnings before interest, taxes, depreciation, and amortization) divided by total assets, and it serves as a critical financial metric for evaluating a firm's operational efficiency and profitability (Jadiyappa et al. 2019). As emphasized by Brealey et al. (2006) and Damodaran (2001), ROA is commonly used by firms to assess their performance, falling under the category of profitability ratios. This ratio evaluates a firm's capacity to generate earnings in relation to its total assets, emphasizing the interplay between profitability and asset utilization. It provides valuable insights into how effectively a company utilizes its asset base to generate income, thereby reflecting its operational prowess and financial performance. Another alternative outcome measure is given by Total Factor Productivity (TFP), whose computation is fully described in Appendix A2.

The key explanatory variable is $s_{i,t}^{IM}$, representing the share of immigrants in the firm's workforce. Consistent with Kim (2007), this migration share variable is defined as the ratio of foreigners to the total firm workforce (foreigners and natives). We also include the interaction between $s_{i,t}^{IM}$ and $I_i(k_i \leq k)$, where the latter is a 1/0 dummy variable denoting whether a given firm-level characteristic is above or below the corresponding median. To analyze whether firm productivity depends on productivity or size levels, we utilize interaction terms to capture the effects on firms with productivity or size below the median.

$X_{i,t}$ represents time-varying firm-specific controls, namely *firm age* and *firm size* (in logs); The *firm age* variable is computed as the difference between year t and the birth year, while size is determined by the monthly average employment (Carreira and Teixeira, 2011). Additionally, $age_{i,t}$ is the log mean age of workers.

Furthermore, we include three firm-level variables representing educational attainment: $Educ\_tertiary_{i,t},\ Educ\_secondary_{i,t},\ and\ Educ\_5\ to 9\ years_{i,t}$. These variables denote the share of workers with tertiary degrees, those who graduated from tertiary education institutions or obtained degrees from equivalent institutions such as polytechnics; workers who completed exactly 12 years of full-time school education or its equivalent (secondary); and those with 5–9 years of education or its equivalent, respectively. $Educ\_ \leq 4$ is the omitted group.

$\emptyset_t$ and θ_i year and firm fixed effects, respectively. Although the methodology we use is the same as in Mitaritonna et al. (2017), our data differs in nature. Unlike their paper, which is at the region level, our research is at the firm level, so we do not include region fixed effects. Firm fixed effects capture unobserved time-invariant factors such as sector fixed effects. Since there is no variation in the sector variable or region within each firm, firms are distinctly characterized by a single sector and region, so firm fixed effects would capture all of these factors. Additionally, the Hausman test and the test proposed by Papke and Wooldridge (2023), which is designed to detect the correct fixed effect, indicate that the firm fixed-effects assumptions are satisfied. In practice, to estimate fixed effects, we use the *xtreg* command in Stata with the within regression estimator. The definitions of variables are fully provided in Appendix Table A.3.

Trends in LP, ROA and TFP

In Figure 4 we plot the growth of labor productivity (LP), Return On Assets (ROA), and Total factor productivity (TFP) over time by taking the mean of the growth for each year across the entire firms. In the three panels depicting the growth of LP, ROA, and TFP, a similar pattern emerges. All three show an upward trend following a notable decline, with LP, ROA, and TFP peaking in 2013. The period from 2012 to 2013 marks a significant increase in growth. The shared decline may have signaled a challenging economic environment, a sentiment reflected in the trends observed in the three plots. Subsequently, from 2013 onwards, there are fluctuations in the plots, though they never regress to the levels observed during the decline in 2012. This trend persists until 2018, with the final year displaying a slight and smooth change.

[Insert Figure 4 here]

To examine how labor productivity (LP) growth varies according to firm characteristics such as productivity levels and size, we present Figure 5. This figure offers a view of LP growth across four distinct types of firms—less productive, productive, small, and large—over the period spanning 2010 to 2019. By analyzing these trends, we gain insights into how productivity evolves based on firm productivity levels and sizes over time. To categorize the firms, we initially compute the median for productivity and size. Using these medians, we establish thresholds for categorization. For productivity, firms are classified as less productive if their productivity levels fall below the median, and as productive if they exceed it. Similarly, for size, firms are categorized as small if their size is below the median, and as large if it surpasses the median. To distinguish between these categories, we employ a dummy variable 1/0 assignment. This method enables clear differentiation between less productive and productive firms based on their productivity levels, as well as between small and large firms based on their sizes.

The growth of LP among less productive and small firms follows similar trends. Both experienced a sudden decline in 2012, followed by a sharp increase until reaching their peak around 2015-2016. Subsequently, they gradually decline until the end of the period. Conversely, the growth pattern of productive firms exhibits more drastic fluctuations. Initially, there is a sharp increase, reaching a peak in 2013. However, they cannot maintain this position, experiencing a significant drop the following year, resulting in the lowest growth in 2018. Large firms show a somewhat different pattern characterized by fluctuations with sharp ups and downs. Similar to productive firms, they peak in 2013. After fluctuations between 2013 and 2017, they experience a sudden decline in 2018, followed by a recovery the next year.

[Insert Figure 5 here]

To further analyze the impact of workforce composition on productivity, we draw upon existing literature, such as Hellerstein et al. (1999) and Jones (2001), which examines how the educational background of workers affects productivity. Our second model implementation addresses the impact of specific immigrants on firm's productivity. As shown in Table 1, there is a significant portion of immigrant workers with an educational background ranging from 5 to 9 years of schooling. This specification arises from the historical context: until 2005, schooling in Portugal was compulsory up to 9 years, after which it was extended to 12 years. By employing this specification, we can distinguish between individuals who completed the previous compulsory schooling and those who did not.

By extending our model to include the share of immigrants with 5 to 9 years of formal education, alongside natives with the same education level, we aim to capture all potential effects of these two subgroups on labor productivity (LP), where the latter are included to ensure that the model accurately attributes effects to the appropriate group. The aim is therefore to elucidate the unique contribution and influence of particular demographic subgroups, as suggested by Lewis (2011). Thus, the model, similar to that of Fassio et al. (2020), is specified as follows:

$$y_{i,t} = \theta_i + \emptyset_t + \beta_1 S_{5\ to\ 9\ years}{}_{i,t}^{IM} + \beta_2 SN_{5\ to\ 9\ years}{}_{i,t}^{N} + \beta_3 X_{i,t} + \beta_4 Educ\_tertiary_{i,t} + \beta_5 Educ\_secondary_{i,t} + \beta_6 age_{i,t} + \varepsilon_{i,t} \quad [2]$$

The model remains consistent with the framework outlined in equation (1), albeit with some notable differences. One such deviation involves the incorporation of two distinct explanatory variables ($S_{5\ to\ 9\ years}{}_{i,t}^{IM}$ and $SN_{5\ to\ 9\ years}{}_{i,t}^{N}$), while excluding the interaction terms. The former variable denotes the proportion of immigrants with 5 to 9 years of formal education whereas the latter represents the share of natives with 5 to 9 years of education, relative to total employment. Unlike model (1), in model (2) we refrain from categorizing firms based on their productivity or employment level. Additionally, another difference between equations (1) and (2) pertains to the education level of workers. Given that the explanatory variables now focus on the shares of immigrants and natives with 5 to 9 years of education, only the $Educ\_tertiary_{i,t}$ and $Educ\_secondary_{i,t}$ terms are included in the model.

We employ fixed effects models with robust standard errors in order to estimate both equations (1 and 2) which address potential sources of endogeneity and unobserved heterogeneity within the panel dataset. However, while the use of fixed effects reduces the impact of unobserved factors present throughout the observation period in our analysis, it is important to acknowledge the potential existence of unobserved factors that may be correlated with both immigrant self-selection and firm's productivity. Specifically, we hypothesize that immigrants may choose to migrate to areas where their compatriots or acquaintances have already settled, intending to benefit from their support and assistance. This phenomenon is indeed a form of self-selection wherein immigrants make choices about their destination based on pre-existing social networks or connections. Immigrant communities often provide valuable support networks that can help newcomers navigate various challenges, such as finding housing, employment opportunities, and cultural integration. Consequently, this form of self-selection may introduce bias into our fixed effect results.

We propose to tackle this issue by examining the geographic dispersion of immigrants across regions, namely by defining the ratio of immigrants from a particular country of origin within a region to the total number of migrants in that region, given by $\frac{IM_{or}}{IM_r}$, where IM_{or} is the number of immigrants from origin *o* in all firms in region *r*, and IM_r is the corresponding total number of immigrant employees. Given that seven country regions are considered in order 1 through 7 (namely, Norte, Centro, Lisboa, Algarve, Alentejo, Açores, and Madeira, respectively), the selected shares therefore indicate the relative importance of a certain ethnic origin in the total foreign workforce in region *r*. In Appendix Tables A.4 and A.5 we present the immigration share by region and country of origin, as well as the overall percentage of immigrant employees by country of origin. The reported shares do show that migrants from specific countries tend to concentrate in particular regions. For instance, Brazilian workers, the largest population of immigrant workers, are dominant in all regions except region 7 (Madeira). In contrast, Venezuelan workers, who are second in the list, exhibit a distinct preference for Region 7, while Indian workers seem to deviate from other nationalities in the sense that they tend to concentrate in regions Norte and Centro. Angolan workers, in turn, despite being among the most populated groups, exhibit a peculiar settlement pattern, are conspicuously scarce in Region 4 and predominant in the capital area (Region 3), as their preferred settlement area.

The proposed instrumental variable (IV) approach draws inspiration from Card (2001) and the observed tendency of newly arrived immigrants to settle in enclaves established by earlier immigrants from the same source country (Bartel 1989). Specifically, we compute: (i) $\frac{IM_{o,r,2010}}{IM_{PT,o,2010}}$, that is, the fraction of immigrants from country *o* living in region *r* 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, $IM_{o,r,2010}$ refers to the total number of immigrants from country *o* living in region *r* 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; and (iii) $Educ_{ost}$, denoting the proportion of immigrant individuals from a particular origin *o* who have a specific levels of education, specifically distinguishing those with 5 to 9 years of education. After aggregating the different country origins, the hypothetical flow of new migrants into region *r*, $\widehat{IM}_{r,t}$, is given by the following equation (differentiated by the types of education) is equal to:

$$\widehat{IM}_{rt} = \sum_{0} \frac{IM_{o,r,2010}}{IM_{PT,o,2010}} * IMM_{ot} * Educ_{ost} \qquad [3]$$

These new flows are used to build two fictional proportions of migrants: one for immigrants with 5 to 9 years of formal education, and another representing the total share of migrants, regardless of education, by summing up the two previous shares. These measures can be used as suitable instruments for the real shares of migrants in equation (1) as well as for the shares of migrants with 5 to 9 years of education in equation (2) within an instrumental variables (IV) framework, as they are expected to exhibit a strong correlation with the observed shares of migrants while remaining uncorrelated with the unobserved shocks of LP. In practice, we employ two-stage least squares 2SLS with *xtivreg2* command in Stata as described in Schaffer (2010).

5. Results

Table 3 displays the regression results obtained from model (1), for the full sample of firms and using Labor Productivity (LP) as the dependent variable. In columns (1) and (2) of the table, the key explanatory variable is the share of foreign-born workers, s^{IM}, while in column (3) it is given by the interaction between s^{IM} and *firms below the median productivity level*, a 1/0 dummy. Similarly in column (4), where the interaction term is given by $s^{IM} \times$ *firms below the median employment level*. As described in Section 4, the regression includes three firm-level variables denoting the education level of the workforce (in three separate groups), the log of the mean age of the workforce, *firm size* (employment) and *firm age* is computed as the difference between year t and the birth year.

[Insert Table 3 here]

The estimate presented in the first column (1) of Table 3 suggests a negative correlation between immigrants and labor productivity, although it is not significantly different from zero. The coefficient derived from the OLS fixed-effects estimation is -0.007, with a standard error of 0.010.

The exercise further reveals the significance of *firm size,* with a negative coefficient of -0.074 (standard error of 0.001). This aligns with the findings of Leung et al. (2008), who similarly observed a negative relationship between firm size and productivity in their research. We find that labor productivity (LP) tends to decrease with *firm age,* although the coefficient is relatively small, measuring 0.096 (with a standard error of 0.002).

Looking at demographic variable, *employee age,* we observe a positive coefficient of 0.01 (0.006), although statistically insignificant. This positive outcome aligns with the findings of Lee et al. (2018), who assert that a positive relationship between older workers and their organizations can enhance firm productivity. However, the lack of statistical significance in the coefficient weakens the support for this notion. In column (1), we also find a positive and statistically significant coefficient of the education level of workers influences labor productivity across all three levels, with the highest impact attributed to the *tertiary education* (0.087 with a standard error of 0.007). This finding suggests that as the workforce becomes more educated, labor productivity levels increase, holding other factors constant. This result is reminiscent of the findings reported by Kampelmann et al. (2018), who similarly observed a positive relationship between education levels and labor productivity in their study.

In summary, all the control variables included in the model are positive and mostly statistically significant, an indication that they are positively associated with a higher productivity level except the *firm size* which has negative impact.

As discussed in the previous section, the share of immigrants in firms is likely to be endogenous due to self-selection among immigrants when choosing their settlements, raising therefore a fundamental concern: the likelihood that the observed relationship between immigrants and the outcome of interest may be influenced by unobserved characteristics or factors related to immigrant self-selection processes. Accordingly, in columns (2) through (4) of the table, we examine the alternative two-stage least squares (2SLS) method with the *xtivreg2* command in Stata.

Thus, in column (2), we instrument the potentially endogenous share of migrants with the fictional share computed through our region-based adaptation of Card (2001) methodology. The analysis does not reveal any significant relationship between LP and *Immigrant share*. The other variables exhibit effects similar to those observed in column (1). To delve deeper into our study, we perform a sector-specific analysis, examining the impact of immigrants on labor productivity across various sectors individually. Our findings indicate that immigrants have a significant and negative effect on labor productivity in both the trade and services sectors. In contrast, the influence on other service sectors appears to be insignificant. Detailed results are given in Appendix A.6.

In column (3), the variable of interest is the interaction between the share of immigrants and firms characterized by productivity levels below the median. In this case, we find that a higher share of immigrants in less productive firms has an adverse impact. Specifically, on average, the decline in the LP for a firm below the median, vis-à-vis a firm above the median, is 0.627 (-1.307 + 0.680 = 0.627) log points for a one percentage point increase in the share of the immigrant, all else being constant. This indicates that firms in this category experience greater challenges from a diverse workforce, particularly with the inclusion of non-local individuals. The positive coefficient for the *Immigrant share* variable in firms initially above the median size indicates an LP increase of 0.680 log points for every one percentage point increase in this variable. The control variables follow a similar pattern as outlined in columns (1) and (2), with only marginal increases in their values corresponding to the education levels of workers.

The negative coefficient for this interaction suggests that while immigrants may enhance productivity firms above the median, their effect is notably negative in low-productivity firms. This finding is supported by two main reasons. First, data analysis reveals that immigrants constitute approximately 5.1% of the workforce in firms with productivity levels below the median, contrasting with around 3.97% in firms with productivity levels above the median. Second, research by Åslund et al. (2023) indicates that the association between a firm's productivity and the proportion of immigrants it employs could be influenced by peer density, potentially leading to thresholds for immigrants' progression along the productivity ladder. Various factors, such as language barriers or managerial hiring practices influenced by ethnic considerations (Åslund et al., 2014), may contribute to these thresholds.

Furthermore, drawing from Lewis (2011), the presence of low-skilled immigrants correlates with the adoption of technologies tailored to unskilled labor-intensive processes requiring minimal skills. In our case where a significant portion of immigrants, specifically 85% of all immigrants, are engaged in low-skilled occupations, firms often tend to adjust their technological frameworks and production methods to accommodate the available workforce. In industries characterized by a substantial influx of low-skilled immigrants, less productive firms, in particular, may lean towards adopting technologies that heavily rely on manual labor and are less mechanized. But it seems, however, that unskilled immigrant workers are not fully aligned with the technological requirements and production practices favored by less efficient and smaller firms. This mismatch is possibly leading to a lower productivity growth within these firms. For more productive firms, there seems to be no such a mismatch.

In addition, Pholphirul and Rukumnuaykit (2017), approaching the issue from a cost-saving perspective, suggest that low-productivity firms may hire less productive and unskilled immigrants to save costs, prioritizing immigrant recruitment due to the perceived affordability of low-skilled labor. However, this strategy can lead to decreased productivity due to skill mismatches, as many low-skilled immigrants lack the necessary training for their assigned tasks. This ultimately undermines overall productivity within the firm.

Finally, in column (4), firms are again separated into two groups, now using their employment size, namely below and above the median. As can be seen, the coefficient in row (1) is now negative, while the interaction term is positive. As a result, on average, the additional LP for a firm below the median, vis-à-vis a firm above the median, is 0.088 (-0.099 + 0.187 = 0.088) log points for a one percentage point increase in the share of immigrant, all else being constant. These findings are in line with those reported by Mitaritonna et al. (2017), who found that firms with below-median employment experienced a TFP increase of 0.351 log points for each one percentage point increase in the immigrant population within the district. In contrast, firms with employment above the median size experienced a decrease of 0.099 log points for each one percentage point increase in the share of immigrants.

This positive role of immigrants in small firms can be attributed to the distinctive characteristics of small firms, as emphasized by Taymaz (2005). Small firms are known for their flexible organizational structures and lack of hierarchical constraints, which may facilitate the integration and utilization of immigrant labor more effectively. Additionally, small firms are less prone to the agency problem, where conflicts of interest between managers and shareholders can lead to inefficiencies. As a result, small firms may be better equipped to leverage the diverse skill sets and perspectives that immigrants bring, leading to positive productivity. Therefore, argument relies on the idea that small firms are not necessarily low in productivity. Leung et al. (2008) support this notion, indicating that while large firms are typically more productive than small firms in certain service industries, such as wholesale trade and accommodation, small firms may exhibit relatively higher productivity levels in retail trade and other service sectors. Therefore, they do not make a firm conclusion that small firms are necessarily less productive. Further supporting this idea, the research data indicates that 51% of firms with productivity levels above the median were categorized as small firms, while 66% of less productive firms fell into the small firm category. This data suggests that small firms can indeed be competitive in terms of productivity, challenging the assumption that larger firms are always more productive.

Using instrumental variables (IV) estimation 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 demonstrate the relevance of these instrumental variables, 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.

The dependent variables, delineated at the top of each column (1)–(5), alongside its interactions with $\mathrm{I_i}(\mathrm{k_i} \leq \mathrm{k})$. In order to show the relevance of the so built instrumental variables, we test the Kleibergen and Paap (2006) rank LM statistic, resilient to heteroskedasticity or autocorrelation, uniformly rejects the null hypothesis of underidentification, thereby the relevance of all instruments is assured. To strengthen this evidence, we conduct weak identification tests using the Cragg-Donald Wald (1993) and Kleibergen-Paap (2006) rank Wald F-statistics. The null hypothesis for these tests is that the instrumental variables are weakly correlated with the endogenous variables. The high F-statistic obtained from the Cragg-Donald Wald test suggests a strong correlation between the instrumental variables and the endogenous variables. Additionally, the F-statistic values from the Kleibergen-Paap rank Wald consistently exceed critical thresholds (as indicated in the Table 4) established by Stock and Yogo (2005). Finally, the overidentification test by Hansen (1982) concludes with the non-rejection of the null hypothesis, indicating the absence of instrument correlation with the error term. Collectively, these findings consistently showcase highly significant instrumental variables' contributions in explaining the endogenous share of immigrants within firms.

[Insert Table 4 here]

Our main empirical strategy now is to estimate an equation like model (1) using, alternatively, Return On Assets (ROA) as the dependent variable, consistent with prior literature (e.g., Shrader et al., 1997; Erhardt et al., 2003). We report the result of this estimation in Table 5. Each column presents the results of a separate regression, which includes workers' educational attainment (categorized into three levels) and their age (transformed logarithmically). Additionally, firm-specific attributes like the logarithm of size (employment) and age are incorporated.

The impact of immigrants on ROA is consistently negative and insignificant, showing no significant deviation from zero in both OLS and IV estimations. This aligns with the OLS and 2SLS results presented in Table 3. Although the control variables in these columns generally show positive and statistically significant relationships, there is a notable exception with the variable *Employee age*. In both columns (1) and (2), a negative effect of approximately -0.68 (0.007) is observed, which contradicts the positive and insignificant findings presented in Table 3. The tests for the validity of the instrumental variables are provided at the bottom of Table 3 clearly reveal robust evidence for the existence of an enclave effect. This effect is identified as the source of correlation between the instrument and the migration share.

In column (3), we continue our analysis by stratifying the sample based on firms performing below the median ROA. We introduce the interaction term *Immigrant share* × *ROA below the median*, a 1/0 dummy. Notably, the coefficients of interest mirror those in Table 3, column (3), albeit with marginally reduced magnitudes, while maintaining statistical significance. Specifically, the decline in the ROA for a firm below the median, vis-à-vis a firm above the median, is 0.498 (in Table 3, column (3) is 0.627) log points for a one percentage point increase in the *Immigrant share*, all else being constant. Furthermore, the control variables demonstrate a significant impact, aligning with previous observations in columns (1) and (2). It is worth noting that significant and positive coefficients for the *education level* variable are observed only for *5–9 years of formal education* variable across all three columns, while the rest do not show statistical significance. *Secondary education* variable also shows statistical significance in column (3), whereas other categories do not.

Following Table 3, in column 4, we classified firms based on those performing below the median employment. The result for the *Immigrant share × employment below the median* variable turns negative. The point estimate indicates that, on average, the decline in ROA for a firm below the median, vis-à-vis a firm above the median, is 0.003 log points for a one percentage point increase in the share of the immigrant, all else being constant. Nevertheless, the findings for the rest of the control variables remain consistent.

These results highlight two key points. Firstly, the importance of selecting an appropriate benchmark for firm performance, which can influence the observed impact of immigration. Secondly, the estimations with ROA as the dependent variable yielded results consistent with those obtained when using LP as the dependent variable. Although the magnitudes of the coefficients in the ROA estimations are smaller than those in the LP estimations, the signs remain the same. This consistency in the direction of the effects suggests that the relationships observed are robust across different measures of firm performance. Hence, regardless of whether LP or ROA is used as the dependent variable, the results indicate similar patterns of influence, reinforcing the reliability of the findings.

[Insert Table 5 here]

Further robustness checks

In our study, given that the majority of immigrants in our dataset are less skilled and are primarily employed in less skilled jobs, it is challenging to predict how they might influence capital intensity. To ensure the reliability of our analysis, we replicate our analyses using the logarithm of total factor productivity (TFP) instead of labor productivity. It is worth noting that changes in capital intensity can affect labor productivity and TFP differently. While an increase in capital intensity typically boosts labor productivity, this does not necessarily mean a corresponding rise in TFP. The overall shift in TFP hinges on the specific output elasticities of both labor and capital.

We deploy model (1) using Total Factor Productivity (TFP) as the dependent variable rather than labor productivity, the corresponding results are given in Table 6. In column (1), running OLS-FE reveals a coefficient of -0.002 (s.e. = 0.001) for the *Immigrant share* variable, which aligns with the findings in Table (3), but notably, it is now statistically significant.

Furthermore, the coefficients of the control variables exhibit a similar pattern observed in Table 5 when the dependent variable is ROA, albeit with trivial values. The education level variables for workers are statistically significant and positive, yet their magnitudes are negligible. We employed instrumental variables by utilizing the fictional share computed in Section 3 to address potential endogeneity issues associated with the migrant share. The estimated effect underwent marginal change, now reaching -0.008 (0.004). Analyzing the results of the validity tests for the instrument, underidentification, and weak identification tests, reported at the bottom of Table 3, leads us to conclude that the instrumental variables employed in the analysis are both valid and robust, as the test statistics exceed the critical values.

In column (3), with the introduction of the interaction term between the share of immigrants and firms characterized by total factor productivity (TFP) levels below the median, we observe interesting patterns. The coefficient for the *Immigrant share* variable is positive and significant

(0.053 with standard error of 0.003), consistent with Table 3. Additionally, the coefficient for *Immigrant share × TFP below the median* variable is negative and significant (-0.145, standard error of 0.004), albeit with a smaller magnitude compared to Table 3 (-1.307, standard error of 0.018). Specifically, on average, the decline in the TFP for a firm below the median, vis-à-vis a firm above the median, is 0.092 log points for a one percentage point increase in the share of immigrant, all else being constant. However, the behavior of other control variables aligns with the patterns observed in previous columns.

In column (4), the coefficient for the interest variable *Immigrant share × employment below median* is positive, although it approaches zero and is significant (0.008, standard error of 0.004). Meanwhile, the coefficient for the *Immigrant share* variable for firms above the maiden size remains negative and significant (-0.013, standard error of 0.005), albeit smaller compared to Table 3. The control variables in this column exhibit a consistent pattern similar to that observed in the preceding columns.

These overall results suggest that the impact of immigrants on productivity, as measured by TFP, is relatively smaller compared to their impact on labor productivity. TFP captures overall productivity taking into account both labor and capital inputs, while LP focuses solely on labor productivity. The smaller coefficient for TFP compared to LP indicates that the relationship between immigrants and productivity, as captured by LP, remains consistent even when employing an alternative measure of productivity (TFP). It could also indicate that immigrants have a greater effect on labor productivity specifically, rather than on TFP that includes other factors such as capital. This could imply that immigrants are particularly effective in enhancing the efficiency of labor inputs but may not have as significant an impact on other factors contributing to TFP.

[Insert Table 6 here]

Unblocking the impact of low-skilled immigrant workers

In this section, our analysis examines the impact of different education groups among immigrants on productivity. Notably, the largest education group among immigrants is comprised of low-skilled individuals, defined as those with a high school education or less (as outlined by Peri and Sparber, 2009). Specifically, immigrants with 5 to 9 years of schooling represent this group, constituting 43% of all immigrants. The emphasis on this group stems therefore from the supposition that unskilled workers potentially have an influence on the adoption of technologies in firms and thereby exerting distinct effects on productivity levels.

To this end, we deploy the model in equation (2) and investigate the role of foreign labor force with 5 to 9 years of formal education, while also considering the contributions of native workers. The results of this investigation are outlined in Table 7. Here, our focus remains on understanding the impact of firm-specific characteristics like age and size. Additionally, we incorporate human capital factors such as the average age and educational composition of employees to capture potential effects arising from age and education levels. This specification differs from previous estimations, as the primary explanatory variable is now the proportion of immigrants with 5-9 years of education relative to total employment. We also include the proportion of natives with 5-9 years of education relative to total employment. Given the limitation of including only three components of total employment in the regression for education level variables, we integrate secondary and tertiary education. The reference group comprises workers with 4 years or less of education. Furthermore, we include firm fixed effects and year dummies in our model to address firm-specific factors that remain constant over time and temporal fluctuations.

Here as well, we begin by presenting the results of the fixed effects estimation, followed by the outcomes of the 2SLS estimation. In the latter, the main explanatory variable, ${S_{5\ to\ 9\ years}}_{\mathrm{i,t}}^{\mathrm{IM}}$, is instrumented by the fictional shares constructed using the methodology detailed in Section 4. We report the results obtained with standard errors robust to heteroscedasticity.

The fixed effects estimation results indicate the positive impact of immigrants with 5 to 9 years of formal education on productivity. The estimated coefficient is 0.060 (with a standard error of 0.011), which is statistically significant. Upon controlling for potential endogeneity, the estimated impacts are still positive, but much larger. Column 2 indicates that for an average firm, a one percentage point increase in the immigrant share correlates with a 0.126 log point increase in LP, holding all other factors constant. This indicates a noteworthy impact of the ${S_{5\ to\ 9\ years}}_{\mathrm{i,t}}^{\mathrm{IM}}$ variable on labor productivity, highlighting the significance of analyzing based on the educational composition of the workforce.

In row 2, the coefficients associated with the share of natives with 5 to 9 years of formal education show a positive and statistically significant relationship in both OLS (0.074) and 2SLS (0.085) models. This underscores the importance of considering native workers to accurately assess the contribution of foreign workers' skills. Based on the theory presented by Peri and Sparber (2009), low-skilled immigrants positively impact productivity by facilitating labor specialization. Immigrants, often possessing strong manual skills but limited language abilities, are well-suited for physically demanding tasks. This allows less-educated native workers, who typically have better communication skills, to focus on language-intensive jobs. As a result, native workers move to roles that offer higher returns, while the overall productivity increases due to the more efficient allocation of labor based on comparative advantage. This shift enhances productivity by maximizing the strengths of both immigrant and native workers. Another explanation for how unskilled immigrant workers influence firm performance, driven by the relative supply of skills, is known as directed technological change (Acemoglu, 1998). Firms that adopt technologies and physical capital tailored to the efficient and intensive use of unskilled labor can see increases in total factor productivity (TFP) in traditional sectors (Peri, 2010, 2012).

To assess the validity of IV, we conduct various tests: The Kleibergen and Paap (2006) rank LM statistic test for underidentification, the Cragg-Donald Wald (1993) and Kleibergen-Paap (2006) rank Wald F-statistics for weak identification, and Hansen (1982) for overidentification. The results of these tests, presented at the bottom of Table 7, indicate the reliability and validity of the instrumental variables used.

The variables of *firm size* and *firm age* consistently exhibit significant effects in both specifications, however, *firm size* has a negative effect just like in Table (3). Looking at the results for the average age of individuals, we find that *employees age* variable displays a positive effect, implying that older employees may possess more experience on the job, thereby positively influencing LP. Additionally, the two variables associated with the share of workers based on educational level consistently exhibit positive and significant effects in both specifications. Notably, the share of tertiary-educated individuals has the largest coefficient, with a value of 0.099 (s.e. = 0.012) in the 2SLS estimation. This suggests that the educational composition of workers is crucial for understanding the contribution of human capital to labor productivity, underscoring the importance of considering educational attainment in workforce composition.

[Insert Table 7 here]

6. Conclusion

Whether foreign workers beneficial or challenging is an important question when trying to uncover the impact of immigration on productivity. It has been difficult to open up the black box of productivity, primarily due to the inherent difficulty in quantifying productivity directly, a challenge exacerbated when considering foreign labor. We use labor productivity (LP) as the chief productivity measure and link employer-employee data from Quadros de Pessoal with firm-level balance sheet data from SCIE-Sistema de Contas Integradas das Empresas, to shed light on the relationship between immigration and firm productivity. Our first set of results, from a fixed effects implementation, with the share of immigrants defined as the proportion of migrants in firm employment, shows no impact on productivity. In order to account for the possible endogeneity of the immigrant share variable, based on the evidence that newly arriving immigrants tend to settle in enclaves formed by earlier immigrants from the same source country, we then proceeded with the well-known procedure implemented by Card (2001). We therefore consider the hypothesis that foreigners tend to migrate to regions in which their compatriots have already settled. The corresponding two-stage least squares analysis did not, however, reveal any correlation between immigrants and firm productivity. This is the first result, which confirms that immigrants do not contribute to the productivity of the firms where they are employed.

The next step involved conducting an in-depth examination of the impact of foreign workers on different firm layers, based on productivity and size. Firstly, we assess the effects of immigration on firms falling below certain threshold, namely the median productivity level. Our results reveal that for less productive firms the impact is negative, with, specifically, a one percentage point increase in the immigrant share being associated with a 0.627 log point decrease in labor productivity for an average firm below the median, vis-à-vis a firm above the median, all else constant. These firms often have limited capital and resources, less structured organizations, and a more conservative working environment, making it challenging for non-local individuals to integrate effectively. However, using the median firm size as an alternative threshold, smaller firms below the median size exhibit a positive effect. More precisely, the additional LP for a firm below the median, compared to a firm above the median, is 0.088 log points for a one percentage point increase in the share of immigrant, all else being constant. As an alternative measure of firm performance, we also deployed the Return on Assets (ROA) variable, with the results of this analysis revealing a striking similarity to those obtained from the labor productivity regression, albeit with slightly smaller effect sizes. Our third measure of firm performance is given by the total factor productivity (TFP), and again despite the change in the magnitude of the relevant coefficients, the results hold.

Finally, given the predominance of unskilled immigrants, we conducted an estimation to evaluate the impact of unskilled immigrants with 5 to 9 years of schooling on productivity levels. Here the presumption is that foreign workers with a low-skilled level may influence the adoption of unskilled-intensive technologies. Our regression analysis yields a significantly positive effect. Specifically, the 2SLS results indicate that for every one percentage point increase in the share of immigrants with 5 to 9 years of education, LP increases by 0.126 log points, holding all other factors constant. In simpler terms, a higher proportion of low-skilled immigrants in the workforce corresponds to higher levels of labor productivity.

Our findings underscore the heterogeneous impact of immigration on productivity, varying significantly with firm characteristics such as productivity and size. The negative impact of immigrants on labor productivity in less productive firms suggests that managers of these firms should focus on improving the integration of immigrant workers and maximizing their potential contributions. On the other hand, small firms benefiting from the positive impact of foreign labor should capitalize on this advantage by fostering inclusive work environments and leveraging diverse skills through targeted recruitment and retention practices. Additionally, immigrants with 5 to 9 years of education (low-skilled workers) showed a positive impact on labor productivity. Policymakers need to recognize the varied impacts of immigration and develop policies that support both low- and high-productivity firms in integrating immigrant labor effectively. Enhancing support for training and integration programs could help mitigate the negative effects observed in less productive firms while leveraging the positive impacts seen in more productive firms and small firms where immigrants contribute positively regardless of their specific educational background.

Our study has limitations, such as the challenge of capturing all dimensions of productivity and the potential influence of unobserved variables. Additionally, fully accounting for aspects like innovation and R&D within productivity measures remains difficult. Moreover, incorporating more recent data could reveal the effects of newer immigration trends, as the increasing influx of recent immigrants might exhibit different characteristics and influences on productivity.

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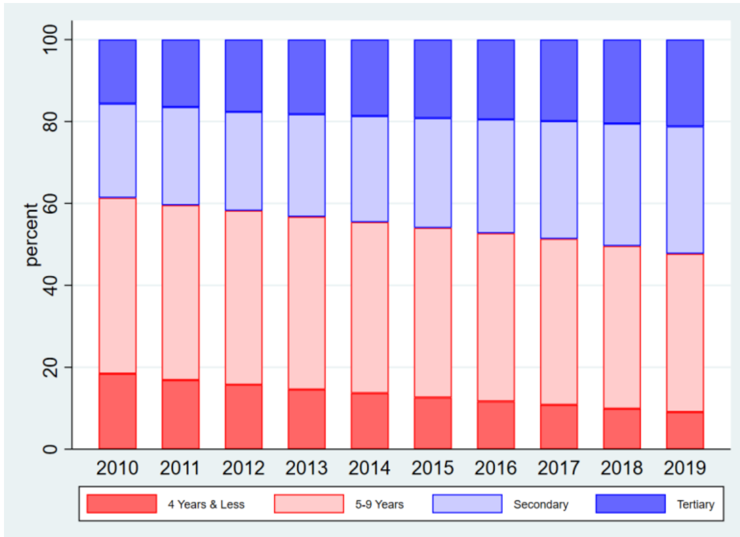
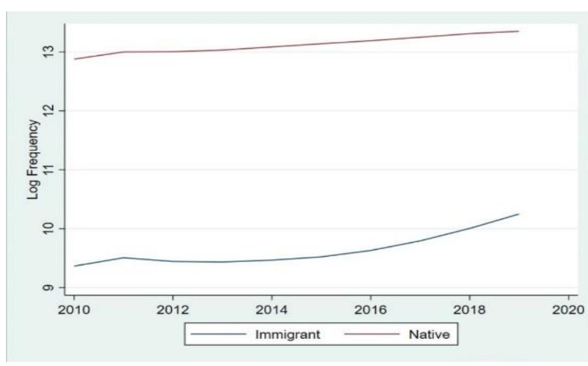
Figure 1. Composition of immigrants by education category



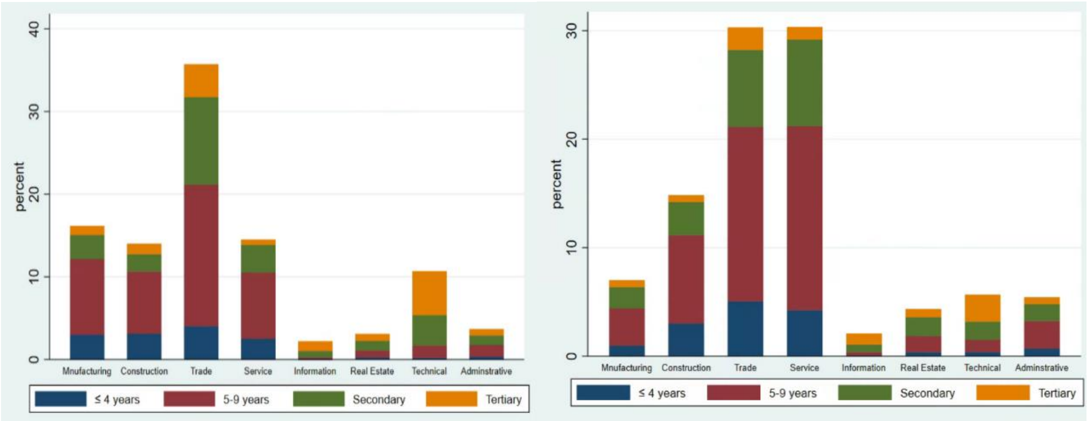
Source: Quadros de Pessoal, 2010 to 2019.

Figure 2. Trend of native and non-native with tertiary education



Notes: The figure illustrates the distribution of workers with tertiary education in firms under examination over the period 2010 to 2019. The y-axis represents the natural logarithm of the count of workers with tertiary education. Immigrants are depicted by the blue line, while natives are represented by the red line. These computations are based on data obtained from the Quadros de Pessoal (QP) database.

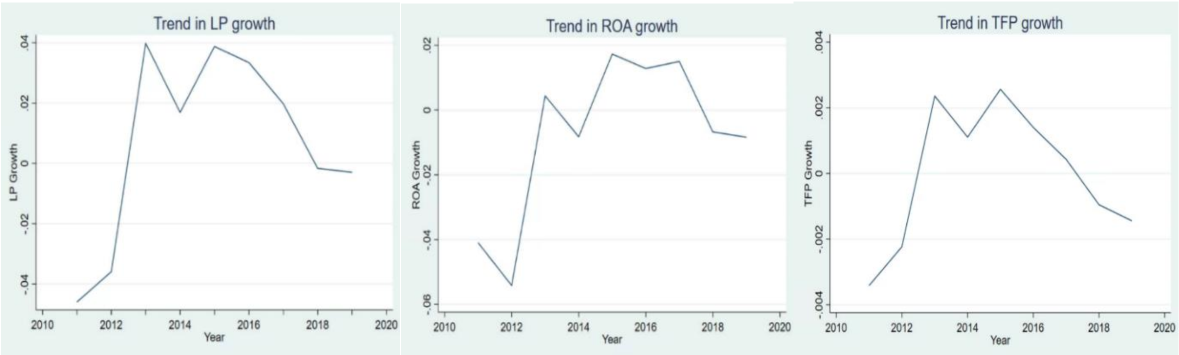
Figure 3. Distribution of workers across sectors by educational group



Panel A: Natives Panel B: Immigrants

Notes: Each panel displays the educational composition of the workforce across four educational groups: individuals with 4 years or less of formal education, those with 5–9 years of formal education, secondary education, and tertiary education. These groups are represented by four distinct colors and are depicted across various manufacturing and service sectors. We excluded other sectors due to differences in the characteristics of the firms, especially regarding financing and production. The y-axis represents percentages, and the data were obtained from the QP and SCIE database, covering the years 2010 to 2019.

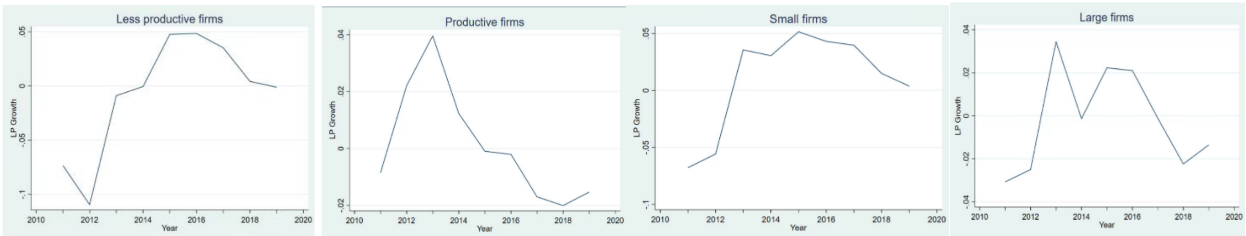
Figure 4. Trends in LP, ROA and TFP growth



Panel A: Trend in LP growth Panel B: Trend in ROA growth Panel C: Trend in TFP growth

Notes: All three panels, A, B, and C, depict the growth of LP, ROA, and TFP by computing the mean of the growth for each year across all firms. The data spans the period from 2010 to 2019.

Figure 5. Analyzing labor productivity trends across firm types: Insights from 2010-2019 data



Note: The figures present an overview of the growth of labor productivity (LP) across four distinct firm types: less productive, productive, small, and large firms. We define less productive firms as those with productivity levels below the median and productive firms as those with productivity levels above the median. Similarly, small firms are those with a size below the median, while large firms have a size above the median. To determine these thresholds, we use a dummy variable (1/0) based on the median characteristics of the firms. The data covers the period from 2010 to 2019.

Table 1 —Descriptive statistics

Variables		Mean	Std. Dev.	Min	Max
At firm-level:					
LP		9.42	1.13	5.51	13.51
ROA		-0.07	0.51	-3.44	1.07
TFP		1.72	0.21	0.75	2.00
Firm age (years)		14.72	15.61	0	521
Firm size (workers)	Number of firms (firm-year):				
<=10	2,422,526	3.06	2.28	0	10
10-250	375,948	33.05	34.92	11	250
>250	9,044	868.40	1588.84	251	25778
At worker level:					
Share of immigrants out of total employment		0.05	0.12	0.00	1
Share by education					
Tertiary education		0.006	0 .031	0.00	1
Secondary education		0.014	0.055	0.00	1
5-9 years of schooling		0.021	0.08	0.00	1
<=4 years of schooling		0.008	0.047	0.00	1
Share of immigrants out of foreign employment.					
Tertiary education		11.82		0.00	1
Secondary education		28.28		0.00	1
5-9 years of schooling		43.65		0.00	1
<=4 years of schooling		16.25		0.00	1
Age		37.50	6.890	18	65
Share of natives out of total employment		0.95		0.00	1
Share by education					
Tertiary education		0.182	0.234	0.00	1
Secondary education		0.254	0.219	0.00	1
5-9 years of schooling		0.391	0.269	0.00	1
<=4 years of schooling		0.124	0.184	0.00	1
Share of natives out of native employment.					
Tertiary education		19.11		0.00	1
Secondary education		26.68		0.00	1
5-9 years of schooling		41.16		0.00	1
<=4 years of schooling		13.04		0.00	1
Age		40.28	6.020	18	65
Year	Number of workers				
2010	2,858,921				
2011	2,845,889				
2012	2,662,123				

2013	2,651,500
2014	2,733,024
2015	2,813,694
2016	2,921,113
2017	3,054,308
2018	3,171,951
2019	3,225,343
Total (worker-year)	27,698,192

Note: The computation of TFP is detailed in the appendix A2. LP, TFP, and ROA variables were winsorized at the 1st and 99th percentiles. The variables TFP and LP are in logarithmic form. The share of immigrants and the employment of natives are presented in decimal form as a proportion of total employment in the firm. Firm's size is given by the average monthly employment.
Sources: SCIE and QP for the period 2010–2019.

Table 2 — Share of immigrants in Portuguese manufacturing and services sectors

Occupation type	Share of foreign workers		
	2010	2019	Change 2010-2019
Skilled (Top 5 cognitive/manual occupation)	0.011	0.025	0.014
Unskilled (bottom 5 cognitive/manual occupation)	0.045	0.053	0.008
Skilled (top 10 cognitive/manual occupation)	0.019	0.032	0.013
Unskilled (bottom 10 cognitive/manual occupation)	0.073	0.082	0.009
Non-production workers	0.024	0.036	0.012
Production workers	0.062	0.070	0.008

Note: The calculations are performed using the QP dataset. We use the O*NET skill taxonomy to classify occupations based on two occupation-specific indices: manual task intensity and communicative task intensity. Within this classification, production workers encompass skilled manual workers, handlers, storage and transport workers, industrial skilled workers, motor-vehicle drivers, unskilled manual workers, and unskilled industrial workers. Other occupational groups are classified as non-production workers. The top 10 occupations ranked by cognitive/manual complexity are as follows: government officials, engineers and technical managers, business and administration professionals, commercial managers, professors and scientist professions, administrative workers in the private sector, teachers, information professions, administrative workers, and technicians. Conversely, the bottom 10 occupations in terms of cognitive/manual complexity include personal services workers, skilled manual workers, skilled handlers, storage and transport workers, foremen, skilled industrial workers, motor-vehicle drivers, unskilled manual workers, and unskilled industrial workers.

Table 3 — The Impact of immigrant share on firm Labor Productivity (LP), OLS-FE and 2SLS estimates, 2010-2019

	Model			
	(1) OLS-FE	(2) 2SLS	(3) 2SLS	(4) 2SLS
Immigrant share	-0.007 (0.010)	-0.0002 (0.023)	0.680*** (0.022)	-0.099*** (0.030)
Immigrant share ×LP below median			-1.307*** (0.018)	
Immigrant share × employment below median				0.187*** (0.027)
Firm size	-0.074*** (0.001)	-0.074*** (0.002)	-0.073*** (0.002)	-0.071*** (0.002)
Firm age	0.096*** (0.002)	0.096*** (0.002)	0.091*** (0.002)	0.096*** (0.002)
Employee age	0.010 (0.006)	0.010 (0.008)	0.007 (0.008)	0.010 (0.008)
Education level of all workers, natives and non-natives. (reference group: 4 years or less)				
5–9 years of formal education	0.072*** (0.005)	0.072*** (0.006)	0.071*** (0.006)	0.072*** (0.006)
Secondary education	0.076*** (0.006)	0.077*** (0.007)	0.078*** (0.007)	0.076*** (0.007)
Tertiary education	0.087*** (0.007)	0.087*** (0.009)	0.091*** (0.008)	0.087*** (0.009)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Number of year-firm observations	1,514,590	1,464,334	1,464,334	1,464,334
Number of firms	288,156	237,900	237,900	237,900

Notes: The model is given by equation (1). In all specifications, the sample is restricted to workers aged 18–65, with the dependent variable being the natural logarithm of labor productivity. The instrumented variables are *Immigrant share, Immigrant share × LP below median* and *Immigrant share × employment below median.* In each model workers are classified according to their educational background: tertiary education, secondary education, and with 5–9 years of formal education. (The reference category is given by the group of workers who have 4 years of education or less.) The fixed-effect estimator with robust standard errors is applied in the first column using *xtreg* command in Stata, while columns (2)–(4) utilize 2SLS through the *xtivreg2* command. ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively; standard errors are given in parentheses.

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

	Model				
	Table 3, column (2)	Table 3, column (3)		Table 3, column (4)	
	(1)	(2)	(3)	(4)	(5)
	Immigrant share	Immigrant share	Immigrant share × LP below median	Immigrant share	Immigrant share × employment below median
IV	0.227*** (0.001)	0.213*** (0.002)	-0.120*** (0.002)	0.157*** (0.002)	-0.041*** (0.001)
IV × LP below median		0.030*** (0.003)	0.505*** (0.003)		
IV × employment below median				0.267*** (0.004)	0.613*** (0.004)
Observations	1,464,334	1,464,334	1,464,334	1,464,334	1,464,334
F-stat of first stage	15140***	7616***	25720***	9199***	9788***
F-stat (Sanderson-Windmeijer multivariate)	15140***	13864***	81575***	12302***	14208***
Joint Underidentification test (Kleibergen-Paap rank LM statistic) Chi-sq(1)	10,000 ***	10,000***		8752***	
Joint weak identification test: F-stat of Cragg-Donald Wald	140,000	70,000		57,000	
F-stat of Kleibergen-Paap rank Wald (10% maximal IV size):	Critical value: 16.38 15,000	Critical value: 7.03 7406		Critical value: 7.03 6097	
Joint overidentification test: Joint of Hansen J statistic	0.000	0.000		0.000	

Note: In each column, the dependent variable is given by the corresponding endogenous variable(s). The set of control variables is the same as in Table 3. Under identification Test (Kleibergen-Paap rank LM statistic): Null Hypothesis: The instruments are weak and irrelevant in explaining the endogenous variables. Weak Identification Test (Cragg-Donald Wald): Null Hypothesis: The instruments are weak and do not adequately predict the endogenous variables. Over identification Test (Hansen J statistic): Null Hypothesis: The instruments are uncorrelated with the error term and do 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— The Impact of immigrant share on firm Return on Assets (ROA), OLS-FE and 2SLS estimates, 2010-2019

	Model			
	(1)	(2)	(3)	(4)
	OLS-FE	2SLS	2SLS	2SLS
Immigrant share	-0.011 (0.009)	-0.009 (0.021)	0.397*** (0.018)	-0.017 (0.027)
Immigrant share × ROA below median			-0.895*** (0.018)	0.014 (0.027)
Immigrant share × employment below median				
Firm size	0.017*** (0.002)	0.017*** (0.001)	0.015*** (0.001)	0.017*** (0.001)
Firm age	0.035*** (0.002)	0.035*** (0.002)	0.034*** (0.002)	0.035*** (0.002)
Employee age	-0.068*** (0.007)	-0.067*** (0.006)	-0.063*** (0.006)	-0.068*** (0.006)
Education level of all workers, natives and non-natives. (reference group: 4 years or less)				
5–9 years of formal education	0.014** (0.006)	0.014*** (0.005)	0.015*** (0.005)	0.014*** (0.005)
Secondary education	0.008 (0.006)	0.008 (0.005)	0.010* (0.005)	0.008 (0.005)
Tertiary education	-0.0005 (0.007)	-0.0005 (0.006)	0.004 (0.006)	-0.0005 (0.006)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Number of year-firm observations	1,653,264	1,603,247	1,603,247	1,603,247
Number of firms	307,786	257,769	257,769	257,769
Joint Underidentification test (Kleibergen-Paap rank LM statistic) Chi-sq(1)		12,000***	12,000***	9664***
F-stat of Cragg-Donald Wald		170,000	85,000	65,000
F-stat of Kleibergen-Paap rank Wald (10% maximal IV size):		Critical value 16.38 18,000	Critical value 7.03 8806	Critical value 7.03 6783
Joint of Hansen J statistic		0.000	0.000	0.000

Notes: The model is given by equation (1). In all specifications, the sample is restricted to workers aged 18–65, with the dependent variable being the Return On Assets. The instrumented variables *are Immigrant share*, *Immigrant share × ROA below median*, and *Immigrant share × employment below median.* In each model workers are classified according to their educational background: tertiary education, secondary education, and with 5–9 years of formal education. (The reference category is given by the group of workers who have 4 years of education or less.) The fixed-effect estimator with robust standard errors is applied in the first column using *xtreg* command in Stata, while columns (2)–(4) utilize 2SLS through the *xtivreg2* command. ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively; standard errors are given in parentheses.

Table 6— The Impact of immigrant share on firm Total Factor Productivity (TFP), OLS-FE and 2SLS estimates, 2010-2019

	Model			
	(1) OLS-FE	(2) 2SLS	(3) 2SLS	(4) 2SLS
Immigrant share	-0.002** (0.001)	-0.008** (0.004)	0.053*** (0.003)	-0.013*** (0.005)
Immigrant share × TFP below median			-0.145*** (0.004)	
Immigrant share × employment below median				0.008* (0.004)
Firm size	0.027*** (0.000)	0.027*** (0.000)	0.026*** (0.000)	0.027*** (0.000)
Firm age	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Employee age	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)
Education level of all workers, natives and non-natives. (reference group: 4 years or less)				
5–9 years of formal education	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)
Secondary education	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
Tertiary education	0.005*** (0.001)	0.005*** (0.001)	0.006*** (0.001)	0.005*** (0.001)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Number of year-firm observations	927,086	859,710	859,710	859,710
Number of firms	233,734	166,358	166,358	166,358
Joint Underidentification test (Kleibergen-Paap rank LM statistic) Chi-sq(1)		5016***	4756***	4243***
F-stat of Cragg-Donald Wald		71,000	33,000	28,000
F-stat of Kleibergen-Paap rank Wald (10% maximal IV size):		Critical value 16.38 7191	Critical value 7.03 3310	Critical value 7.03 2929
Joint of Hansen J statistic		0.000	0.000	0.000

Notes: The model is given by equation (1). In all specifications, the sample is restricted to workers aged 18–65, with the dependent variable being the natural logarithm of TFP, computed using the Levinsohn and Petrin method. The instrumented variables are *Immigrant share, Immigrant share × TFP below median* and *Immigrant share × employment below median.* In each model workers are classified according to their educational background: tertiary education, secondary education, and with 5–9 years of formal education. (The reference category is given by the group of workers who have 4 years of education or less.) The fixed-effect estimator with robust standard errors is applied in the first column using *xtreg* command in Stata, while columns (2)–(4) utilize 2SLS through the *xtivreg2* command. ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively; standard errors are given in parentheses.

Table 7— Impact of immigrants by education groups on labor productivity

	Model	
Variables	(1) OLS-FE	(2) 2SLS
Immigrant share with 5-9 years of formal education	0.060*** (0.011)	0.126** (0.059)
Native share with 5-9 years of formal education	0.074*** (0.005)	0.085*** (0.010)
Firm size	-0.074*** (0.001)	-0.080*** (0.002)
Firm age	0.096*** (0.002)	0.097*** (0.002)
Employee age	0.010 (0.006)	0.017* (0.010)
Education level of all workers, natives and non-natives. (reference group: 4 years or less)		
Secondary education	0.076*** (0.006)	0.090*** (0.012)
Tertiary education	0.087*** (0.007)	0.099*** (0.012)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Number of year-firm observations	1,514,590	1,372,355
Number of firms	288,156	231,181
Joint Underidentification test (Kleibergen-Paap rank LM statistic) Chi-sq(1)		3311***
F-stat of Cragg-Donald Wald		65000
F-stat of Kleibergen-Paap rank Wald Critical value (10% maximal IV size):		3591 16.38
Joint of Hansen J statistic		0.000

Notes: The model is given by equation (2). In all specifications, the sample is restricted to workers aged 18–65, with the dependent variable being the natural logarithm of labor productivity. The instrumented variable is *Immigrant share with 5-9 years of formal education*. In each model workers are classified according to their educational background: tertiary education and secondary education. (The reference category is given by the group of workers who have 4 years of education or less.) The fixed-effect estimator with robust standard errors is applied in the first column using *xtreg* command in Stata, while columns (2)–(4) utilize 2SLS through the *xtivreg2* command. ***, ** 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- ONET 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: Domain names are sourced from the 'O*NET Content Model', 2018.

Appendix Table A.2— The educational composition of foreign-born workers across sectors

Variables	Percent
Manufacturing	
Immigrant share with ≤ 4 years of formal education	13.94
Immigrant share with 5-9 years of formal education	48.68
Immigrant share with secondary education	28.08
Immigrant share with tertiary education	9.30
Number of immigrants	7,632
Trade	
Immigrant share with ≤ 4 years of formal education	16.68
Immigrant share with 5-9 years of formal education	53.07
Immigrant share with secondary education	23.43
Immigrant share with tertiary education	6.82
Number of immigrants	33,022
Accommodation	
Immigrant share with ≤ 4 years of formal education	13.96
Immigrant share with 5-9 years of Schooling	55.90
Immigrant share with secondary education	26.28
Immigrant share with tertiary education	3.86
Number of immigrants	33,075
Construction	
Immigrant share with ≤ 4 years of formal education	20.26
Immigrant share with 5-9 years of formal education	54.96
Immigrant share with secondary education	20.56
Immigrant share with tertiary education	4.22
Number of immigrants	16,167
Real estate	
Immigrant share with ≤ 4 years of formal education	8.56
Immigrant share with 5-9 years of formal education	33.90
Immigrant share with secondary education	40.26
Immigrant share with tertiary education	17.28
Number of immigrants	4,729
Business services	
Immigrant share with ≤ 4 years of formal education	8.81

Immigrant share with 5-9 years of formal education	30.06
Immigrant share with secondary education	29.88
Immigrant share with tertiary education	31.24
Number of immigrants	14,359

Notes: The table displays the proportion of immigrants categorized by their educational achievements within each sector relative to the total immigrant population within that specific sector. The Business service sector comprises Information and communication, Professional, scientific and technical activities, and Administrative and support service activities. The computations are based on the QP and SCIE dataset for the period 2010–2019.

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

Variable	Definition	Mean
Labour productivity (LP)	It is defined as gross value added (GVA) per worker, calculated as the difference between gross output and material inputs (in logs).	9.412
Return On Asset (ROA)	It is calculated as EBITDA (earnings before interest, taxes, depreciation, and amortization) divided by total assets.	-0.181
Total factor productivity (TFP)	TFP is computed as a residual in productivity analysis. It is computed through the semi-parametric method proposed by Levinsohn and Petrin (2003).	1.989
Immigrant share	The share of immigrants in the firm's workforce. It is defined as the ratio of foreigners to the total firm workforce (foreigners and natives).	0.050
Immigrant share with 5-9 years of formal education	It is defined as the ratio of immigrants with 5–9 years of education to the total firm workforce (foreigners and natives).	0.024
Native share with 5-9 years of formal education	It is defined as the ratio of natives with 5–9 years of education to the total firm workforce (foreigners and natives).	0.420
LP below the median	1/0 dummy variable: We compute the median of LP for the entire sample and assign a value of 1 if the LP of a firm is below the median.	0.499
Immigrant share ×LP below median	Interaction between Immigrant share and LP below median.	0.023
TFP below the median	1/0 dummy variable: We compute the median of TFP for the entire sample and assign a value of 1 if the TFP of a firm is below the median.	0.420
Immigrant share ×TFP below median	Interaction between Immigrant share and TFP below median.	0.016
ROA below the median	1/0 dummy variable: We compute the median of ROA for the entire sample and assign a value of 1 if the ROA of a firm is below the median.	0.500
Immigrant share ×ROA below median	Interaction between Immigrant share and ROA below median.	0.022
employment below the median	1/0 dummy variable: We compute the median of employment for the entire sample. If a firm's employment is below the median, it is assigned a value of 1.	0.864
Immigrant share × employment below median	Interaction between Immigrant share and employment below the median.	0.028
Firm size	It is determined by the monthly average employment (in logs).	1.228
Firm age	It is computed as the difference between year t and the birth year (in logs)..	2.298
Employee age	It is the log mean age of workers (foreigners and natives)	3.712
Share of workers with 4 or less years of formal education	The share of workers with 4 or less years of formal education as a proportion of total employment in the firm.	0.141
Workers share with 5–9 years of formal education	The share of workers with 5–9 years of education as a proportion of total employment in the firm.	0.444
Workers share with secondary education	The share of workers with secondary education as a proportion of total employment in the firm.	0.257
Workers share with tertiary education	The share of workers with tertiary degrees as a proportion of total employment in the firm.	0.158

Note: LP, TFP, and ROA variables were winsorized at the 1st and 99th percentiles. Our estimation sample comprises firms operating in the Manufacturing, Trade, Accommodation, Construction, Real Estate, and Business Services sectors. The regions included are Norte, Centro, Lisboa, Algarve, Alentejo, Açores, and Madeira. The analysis covers the period from 2010 to 2019.
Sources: SCIE and QP.

Appendix Table A.4— Ethnic share

Nationality	Rank	Region	Immigrant share (sum)
Brazil	1	3	0.275
Brazil	1	4	0.210
Brazil	1	2	0.258
Brazil	1	6	0.209
Brazil	1	1	0.264
Brazil	1	5	0.166
Venezuela	1	7	0.178
Brazil	2	7	0.143
Cape Verde	2	3	0.134
Cape Verde	2	6	0.144
Romania	2	5	0.128
Ukraine	2	4	0.161
Ukraine	2	2	0.238
Ukraine	2	1	0.129
Spain	3	1	0.073
Romania	3	2	0.062
Romania	3	4	0.108
Ukraine	3	7	0.088
Ukraine	3	6	0.096
Ukraine	3	3	0.065
Ukraine	3	5	0.126
Angola	4	3	0.063
China	4	7	0.051
China	4	6	0.094
China	4	1	0.062
India	4	5	0.078
Moldova	4	4	0.057
Moldova	4	2	0.040
Bulgaria	5	5	0.067
China	5	2	0.035
Cape Verde	5	1	0.060
United Kingdom	5	4	0.055
Romania	5	3	0.049
Romania	5	7	0.050
United States	5	6	0.063
Canada	6	6	0.040
Cape Verde	6	4	0.051
Cape Verde	6	2	0.035
France	6	1	0.048
France	6	7	0.040
Guinea-Bissau	6	3	0.047
Nepal	6	5	0.052
Angola	7	1	0.047
Angola	7	2	0.035
China	7	5	0.046
Germany	7	7	0.037

Spain	7	6	0.032
India	7	4	0.039
Sao Tome and Principe	7	3	0.037
China	8	3	0.032
Germany	8	6	0.031
France	8	2	0.032
United Kingdom	8	7	0.035
Nepal	8	4	0.029
Romania	8	1	0.031
Thailand	8	5	0.044
Angola	9	6	0.025
Germany	9	4	0.027
Spain	9	5	0.042
Spain	9	3	0.027
Italy	9	7	0.032
Venezuela	9	1	0.022
Venezuela	9	2	0.022
Bulgaria	10	4	0.024
Guinea-Bissau	10	1	0.021
India	10	2	0.021
Moldova	10	5	0.038
Macao	10	6	0.021
Nepal	10	3	0.026
Russia	10	7	0.032
Cape Verde	11	7	0.030
Cape Verde	11	5	0.033
France	11	3	0.024
Guinea-Bissau	11	4	0.021
Guinea-Bissau	11	6	0.020
Nepal	11	2	0.017
Sao Tome and Principe	11	1	0.016
Angola	12	5	0.018
Angola	12	7	0.024
China	12	4	0.021
Germany	12	1	0.015
Spain	12	2	0.016
France	12	6	0.019
India	12	3	0.022
Angola	13	4	0.020
Moldova	13	1	0.015
Moldova	13	3	0.020
Pakistan	13	5	0.018
Romania	13	6	0.017
Russia	13	2	0.016
South Africa	13	7	0.022
Bangladesh	14	5	0.016
Guinea-Bissau	14	2	0.015
Guinea-Bissau	14	7	0.019
Italy	14	3	0.016
Mozambique	14	6	0.016

Russia	14	1	0.014
Russia	14	4	0.017
Bulgaria	15	2	0.014
Spain	15	7	0.017
France	15	4	0.014
Guinea	15	3	0.014
Mozambique	15	1	0.014
Poland	15	5	0.013
Russia	15	6	0.014
Spain	16	4	0.014
Guinea-Bissau	16	5	0.011
India	16	1	0.013
Moldova	16	7	0.017
Mozambique	16	3	0.014
Sweden	16	6	0.014
Thailand	16	2	0.014
Germany	17	3	0.013
Italy	17	1	0.012
Italy	17	6	0.014
Mozambique	17	2	0.012
Netherlands	17	5	0.010
Netherlands	17	4	0.014
Sweden	17	7	0.013
Bangladesh	18	3	0.013
Germany	18	5	0.009
Guinea	18	4	0.011
Guinea	18	1	0.011
India	18	7	0.011
Sao Tome and Principe	18	2	0.011
United Kingdom	18.500	6	0.012
Sao Tome and Principe	18.500	6	0.012
Bulgaria	19	1	0.010
Germany	19	2	0.010
France	19	5	0.009
United Kingdom	19	3	0.011
Morocco	19	4	0.010
Mozambique	19	7	0.010
Bermuda	20	6	0.008
United Kingdom	20	1	0.009
Guinea	20	7	0.010
Italy	20	4	0.009
Mozambique	20	5	0.008
Russia	20	3	0.009
Uzbekistan	20	2	0.007
Stateless	21	1	0.009
Bangladesh	21	4	0.008
Bulgaria	21	3	0.008
Italy	21	2	0.006
Moldova (Republic of)	21	6	0.007
Pakistan	21	7	0.007

São Tomé and Príncipe	21	5	0.006
Guinea	22	2	0.006
Pakistan	22	3	0.008
Pakistan	22	4	0.007
Poland	22	1	0.006
Puerto Rico	22	6	0.005
Russia (Russian Federation)	22	5	0.006
São Tomé and Príncipe	22	7	0.007
United Kingdom	23	2	0.006
Italy	23	5	0.005
Morocco	23	1	0.005
Netherlands	23	3	0.006
Philippines	23	7	0.007
Venezuela (Bolivarian Republic of)	23	4	0.006
Venezuela (Bolivarian Republic of)	23	6	0.005
Guinea	24	5	0.005
Mozambique	24	4	0.005
Nepal	24	1	0.004
Paraguay	24	6	0.004
United States	24	2	0.004
Venezuela (Bolivarian Republic of)	24	3	0.006
Mexico	24.500	7	0.006
Netherlands	24.500	7	0.006
Belgium	25	3	0.004
Canada	25	2	0.004
United Kingdom	25	5	0.004
São Tomé and Príncipe	25	4	0.005
United States	25	1	0.004

Note: The variable *nationality* indicates the birthplace of workers. The variable *rank* in the first column denotes the rank of immigrants' share by region. The computations are based on the QP dataset for the period 2010–2019.

Appendix Table A.5— Foreign worker percentages

Nationality	Immigrants share
Brazil	24.767
Ukraine	11.460
Cape Verde	9.684
Romania	6.268
Angola	4.909
China	3.737
Guinea-Bissau	3.401
Spain	3.061
Moldova	2.831
France	2.580
Sao Tome and Principe	2.542
India	2.370
Nepal	2.187
United Kingdom	1.558
Bulgaria	1.537
Germany	1.506
Italy	1.241
Mozambique	1.239
Guinea	1.195
Russia	1.187
Venezuela	1.073
Bangladesh	0.926
Pakistan	0.669
Netherlands	0.663
Thailand	0.591
Poland	0.391
Asia/Pacific Region	0.354
Morocco	0.349
Belgium	0.317
United States	0.301
Senegal	0.296
Uzbekistan	0.201
Cuba	0.200
Canada	0.197
South Africa	0.194
Switzerland	0.186
Sweden	0.161
Georgia	0.153
Colombia	0.124
Philippines	0.123
Lithuania	0.122
Ireland	0.119
Argentina	0.118
Austria	0.113
Kazakhstan	0.109
Hungary	0.097
Belarus	0.094
Turkey	0.079
Mexico	0.076
Denmark	0.074
Netherlands Antilles	0.072
Macau	0.070
Greece	0.069

Latvia	0.066
Czech Republic	0.063
Egypt	0.062
Andorra	0.062
Nigeria	0.060
Finland	0.057
Puerto Rico	0.054
Peru	0.052
Luxembourg	0.049
Paraguay	0.049
Serbia	0.048
Slovakia	0.048
Australia	0.046
Algeria	0.045
Japan	0.044
Iran	0.044
Indonesia	0.043
Norway	0.040
Croatia	0.037
Ecuador	0.036
Tunisia	0.034
Democratic Republic of the Congo	0.033
Zimbabwe	0.033
Chile	0.031
Estonia	0.031
Central African Republic	0.030
French Guiana	0.029
Timor-Leste	0.028
Ghana	0.027
Uruguay	0.027
Panama	0.025
Syria	0.025
Republic of the Congo	0.023
Armenia	0.022
Ivory Coast (Côte d'Ivoire)	0.022
Albania	0.021
Slovenia	0.021
Cameroon	0.021
Dominican Republic	0.019
Gambia	0.017
Bolivia	0.017
Guyana	0.017
Bosnia and Herzegovina	0.017
Guam	0.017
Israel	0.017
Vietnam	0.016
Mali	0.016
South Korea	0.015
Jordan	0.015
Antigua and Barbuda	0.015
Equatorial Guinea	0.014
Sri Lanka	0.014
Sint Maarten (Dutch part)	0.014
Iraq	0.013
Eritrea	0.013
Palestine	0.012
North Macedonia	0.012

Lebanon	0.012
Benin	0.011
Afghanistan	0.011
Guatemala	0.010
Sierra Leone	0.010
American Samoa	0.009
Namibia	0.009
Kyrgyzstan	0.009
Mauritania	0.009
New Zealand	0.008
Costa Rica	0.007
Malaysia	0.007
United Arab Emirates	0.007
Azerbaijan	0.007
Turks and Caicos Islands	0.007
Ethiopia	0.006
Cyprus	0.006
Montenegro	0.006
Honduras	0.006
Palau	0.006
El Salvador	0.005
Gabon	0.005
Niger	0.005
Togo	0.005
Zambia	0.004
British Indian Ocean Territory	0.004
Maldives	0.004
Mongolia	0.004
South Georgia and the South Sandwich	0.004
Islands	0.004
Tajikistan	0.004
Saudi Arabia	0.004
Tanzania	0.004
Monaco	0.004
Eswatini	0.004
Kenya	0.004
Singapore	0.004
Saint Barthelemy	0.004
Bermuda	0.004
Nicaragua	0.004
Malta	0.003
Uganda	0.003
Sudan	0.003
Mauritius	0.003
Burkina Faso	0.003
Libya	0.003
Bhutan	0.003
Jamaica	0.003
Taiwan	0.003
North Korea	0.003
Malawi	0.003
Liberia	0.003
Cambodia	0.002
Aruba	0.002
Brunei	0.002
British Virgin Islands	0.002
Antarctica	0.002

Kosovo	0.002
Liechtenstein	0.002
United States Minor Outlying Islands	0.002
Botswana	0.002
Belize	0.002
Hong Kong	0.002
Curacao	0.002
Samoa	0.002
Tonga	0.002
Iceland	0.002
Madagascar	0.002
Réunion	0.002
New Caledonia	0.002
French Polynesia	0.002
Rwanda	0.002
South Sudan	0.002
Kuwait	0.002
Yemen	0.001
Suriname	0.001
San Marino	0.001
Pitcairn Islands	0.001
Cayman Islands	0.001
Niue	0.001
Comoros	0.001
Bouvet Island	0.001
Papua New Guinea	0.001
Somalia	0.001
Chad	0.001
Saint Pierre and Miquelon	0.001
Marshall Islands	0.001
Myanmar (Burma)	0.001
Martinique	0.001
Qatar	0.001
Bonaire, Sint Eustatius, and Saba	0.001
Montserrat	0.001
Saint Vincent and the Grenadines	0.001
Solomon Islands	0.001
French Southern and Antarctic Lands	0.001
Nauru	0.001
The Bahamas	0.001
Western Sahara	0.001
Turkmenistan	0.001
Tokelau	0.001
Federated States of Micronesia	0.001
Anguilla	0.001
Isle of Man	0.001
Oman	0.001
Vanuatu	0.001
Jersey	0.001
Laos	0.001
Guernsey	0.001
Guadeloupe	0.001
Grenada	0.001
Trinidad and Tobago	0.001
Gibraltar	0.001
Vatican City	0.001
Burundi	0.001

Fiji	0.001
Djibouti	0.001
Bahrain	0.001
Barbados	0.001
Seychelles	0.001
Saint Helena	0.001
Dominica	0.001
Haiti	0.001
Wallis and Futuna	0.001
Åland Islands	0.001
Lesotho	0.001
Faroe Islands	0.001
Falkland Islands	0.000
Cook Islands	0.000
Cocos (Keeling) Islands	0.000
Saint Lucia	0.000

Note: The variable *nationality* indicates the country of origin of workers. The immigrants share gives the percentage of foreign workers in total immigrant population. The computations are based on the QP dataset for the period 2010–2019.

Appendix Table A.6—The impact of immigrant share on firm Labor Productivity (LP) by sector, OLS-FE and 2SLS Estimates, 2010-2019.

	Manufacturing		Construction		Trade		Accommodation		Real estate		Service	
	FE	IV	FE	IV	FE	IV	FE	IV	FE	IV	FE	IV
Immigrant share	0.019 (0.021)	-0.032 (0.077)	-0.020 (0.019)	-0.0267 (0.055)	-0.049*** (0.014)	0.129*** (0.048)	-0.010 (0.015)	0.045 (0.045)	0.033 (0.043)	0.077 (0.119)	-0.030* (0.017)	0.041 (0.051)
Firm size	-0.050*** (0.003)	-0.050*** (0.005)	0.024*** (0.003)	0.024*** (0.004)	-0.086*** (0.003)	-0.086*** (0.003)	-0.089*** (0.005)	-0.089*** (0.006)	-0.225*** (0.011)	0.225*** (0.013)	-0.091*** (0.003)	-0.092*** (0.004)
Firm age	0.058*** (0.004)	0.058*** (0.004)	0.020*** (0.005)	0.020*** (0.005)	0.091*** (0.003)	0.091*** (0.004)	0.117*** (0.006)	0.117*** (0.006)	0.284*** (0.017)	0.284*** (0.019)	0.132*** (0.004)	0.132*** (0.005)
Employee age	-0.074*** (0.015)	-0.075*** (0.020)	-0.057*** (0.019)	-0.057** (0.023)	0.007 (0.010)	0.500 (0.013)	-0.018 (0.017)	-0.012 (0.021)	-0.105** (0.043)	-0.103** (0.049)	0.112*** (0.014)	0.113*** (0.018)
Education level of all workers, natives and non-natives. (reference group: 4 years or less)												
5–9 years of formal education	0.036*** (0.01)	0.035*** (0.013)	0.055*** (0.011)	0.055*** (0.013)	0.071*** (0.009)	0.071*** (0.010)	0.025* (0.013)	0.026* (0.015)	0.034 (0.042)	0.034 (0.048)	0.090*** (0.018)	0.092*** (0.023)
Secondary education	0.0155 (0.012)	0.016 (0.016)	0.0150 (0.014)	0.015 (0.018)	0.083*** (0.010)	0.082*** (0.012)	0.0172 (0.015)	0.019 (0.018)	0.061 (0.043)	0.062 (0.050)	0.115*** (0.019)	0.118*** (0.023)
Tertiary education	0.0238 (0.017)	0.0239 (0.025)	0.027 (0.018)	0.027 (0.025)	0.079*** (0.012)	0.079*** (0.015)	-0.009 (0.023)	-0.006 (0.029)	0.093** (0.046)	0.095* (0.054)	0.168*** (0.019)	0.171*** (0.024)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of year-firm observations	266,645	260,878	213,122	204,282	536,471	520,987	184,029	176,247	49,641	45,990	264,682	254,737
Number of firms	44,241	38,474	44,228	35,388	98,149	82,665	39,038	31,256	12,972	9,321	53,115	43,170
Joint Underidentification test (Kleibergen-Paap rank LM statistic) Chi-sq(1)	997 ***		1975 ***		2407 ***		3022 ***		434 ***		1481***	
F-stat of Cragg-Donald Wald	19,000		22,000		50,000		1600		6621		2800	
F-stat of Kleibergen-Paap rank Wald (10% maximal IV size)	Critical values 16.38 1340		Critical values 16.38 3009		Critical value 16.38 3551		Critical values 16.38 4306		Critical value 16.38 715		Critical value 16.38 2227	
Joint of Hansen J statistic	0.000		0.000		0.000		0.000		0.000		0.000	

Note: In all specifications, the sample is restricted to workers aged 18–65, with the dependent variable being the natural logarithm of labor productivity. Each column reports the results for a specific sector. The instrumented variable is *Immigrant share*. In each model workers are classified according to their educational background: tertiary education, secondary education, and with 5–9 years of formal education. (The reference category is given by the group of workers who have 4 years of education or less.) The fixed-effect estimator with robust standard errors is applied in each column using *xtreg* command in Stata, IV utilize 2SLS through the *xtivreg2* command. ***, ** and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively; standard errors are given in parentheses.

Appendix A1: Occupational groups

Occupations are recorded according to the Portuguese Classification of Occupations (CPP) (2010). We use the first four digits of the occupation variable corresponding to a CPP code to identify occupations. To compose the occupation index, we use data from the O*NET survey (version 27). The US Department of Labor provides comprehensive data on employee and job characteristics through the Occupational Information Network (O*NET) Resource Center. The data is built on surveys of workers, employers and job experts. Despite the excellent quality and quantity of the Portuguese register data, QP, it lacks information on professional characteristics and requirements. We therefore use data on US occupations provided by the O*NET database. To link O*NET data to Portuguese occupations, we manually construct a crosswalk from the Portuguese Occupational Classification System (CPP) to the occupational taxonomy of O*NET yielding a total of 374 unique occupations. Although the O*NET survey supports six distinct areas, we focus on four surveys: workers' skills, knowledge, abilities, and work activities. Table A.3 contains a detailed list of the variables used in the analysis. For instance, 'speaking' involves conveying information effectively to others. The knowledge domain is dedicated to organized sets of principles and facts applicable to general domains. For example, mechanical knowledge pertains to understanding machines and tools, including their designs, uses, repair, and maintenance. The ability domain covers persistent attributes of an individual that influence performance, while verbal ability involves acquiring and applying verbal information to solve problems. Work activities within this context are common across a broad spectrum of occupations, spanning various job families and industries. An example includes assisting and caring for others, which involves providing personal assistance, medical attention, emotional support, or other personal care to individuals such as coworkers, customers, or patients (description derived from the O*NET Content Model, 2022).

In line with the approach outlined by Peri and Sparber (2009), we assume that occupations can be characterized by two occupation-specific indices: manual task intensity and communicative task intensity. Subsequently, individual occupations are categorized based on their relative communicative-to-manual task intensity. Using the O*NET, we calculate two indices, each with two values for each feature: each occupation is assigned an importance value (I) ranging from 0 to 5 and a level value (L) ranging from 0 to 7. Thus, for each occupation (j) and each feature (k), there exists a level value $L_{j,k}$ and an importance value $I_{j,k}$. By classifying the features according to communication features and manual features, we calculate the mean importance value and the mean level value: $\bar{I}_j^{comm}$, $\bar{L}_j^{comm}$, $\bar{I}_j^{man}$, and $\bar{L}_j^{man}$. We then generate manual (TS_j^{manual}) and communicative (TS_j^{comm}) task-intensity values by multiplying the importance value and the level value, the so-called skill ratio for each profession as the ratio of communicative to manual task intensity ($\frac{TS_j^{comm}}{TS_j^{manual}}$), thus defining our professional groups. Following Borjas (2003), to maintain consistency we perform a four-group occupational classification.

Appendix A2: Computing Total Factor Productivity

In order to compute the Total Factor Productivity (TFP), we proceed to estimate a logarithmic Cobb–Douglas production function, (2-digit level), as follows:

$$Ln\,TFP_{i,t} = Ln\,Y_{i,t} - \alpha_K LnK_{i,t} - \alpha_L LnL_{i,t} - \alpha_M LnM_{i,t} \qquad [1]$$

where $Y_{i,t}$ is real output of the firm i in year t, and $K_{i,t}$, $L_{i,t}$ and $M_{i,t}$ denote capital, labor and materials, respectively; and α_f denotes factor elasticities (f = K, L, M). The average number of employees during the year is used as a proxy for labor. Materials were deflated by the GDP deflator index. For real capital we used a perpetual inventory method to the change in total real assets.

To address endogeneity stemming from unobserved variables influencing the firm's decision-making process for choosing inputs (capital and labor), we incorporate the semi-parametric method proposed by Levinsohn and Petrin (2003) into our estimation framework. This approach uses intermediate inputs to represent unobservable productivity, eliminating the need for nonzero investment required by the Olley and Pakes (1996) estimator. This enhances the robustness of our modeling approach and provides a comprehensive solution to endogeneity and unobservable productivity issues in our analysis.