MASTER

MONETARY AND FINANCIAL ECONOMICS

MASTER'S FINAL WORK

DISSERTATION

DO MIGRATION SHOCKS RAISE TFP?
EVIDENCE FROM PRODUCTIVITY DECOMPOSITIONS ACROSS EUROPEAN ECONOMIES

INÊS PIRES ANTUNES

JUN - 2026

MASTER

MONETARY AND FINANCIAL ECONOMICS

MASTER'S FINAL WORK

DISSERTATION

DO MIGRATION SHOCKS RAISE TFP?
EVIDENCE FROM PRODUCTIVITY DECOMPOSITIONS ACROSS EUROPEAN ECONOMIES

INÊS PIRES ANTUNES

SUPERVISION:
JOSÉ ALVES

JUN - 2026

GLOSSARY

AMECO- Annual Macro-Economic Database of the European Commission

CP- Capital Productivity

EU- European Union

GDP- Gross Domestic Product

H-1B- H-1B Visa Program (US temporary work visa for high-skilled foreign workers)

ISCED- International Standard Classification of Education

KI- Capital Intensity

LP- Labour Productivity

OECD- Organisation for Economic Co-operation and Development

SE- Science and Engineering

STEM- Science, Technology, Engineering, and Mathematics

SYS-GMM- System Generalised Method of Moments

TFP- Total Factor Productivity

U.S- United States

USSR- Union of Soviet Socialist Republics

ABSTRACT, KEYWORDS AND JEL CODES

The main objective of this dissertation is to analyse whether migration shocks increase productivity in the economies of the European Union. While migration is typically treated as a one-time shock to the labour supply, its consequences for output can manifest through various channels, including the potential for efficiency gains, changes in capital intensity and the reallocation of factors between labour and capital. Consequently, in order to address this, the analysis I propose to conduct decomposes productivity into four components: total factor productivity (TFP), labour productivity, capital productivity, and capital intensity, by constructing a country-year fixed-effects panel using data from Eurostat and AMECO covering 27 European Union member states between 1998 and 2024.

Regarding the empirical strategy used, it is based on a fixed-effects panel with country and year fixed effects. To complement the main analysis, I also conducted seven robustness tests, including specifications with lags and distributed lags, country-specific trends, and the exclusion of small economies as well as crisis years. As a result, through these tests, it was possible to confirm the main conclusion that, contrary to what some literature suggests, there is no positive and statistically significant relationship between migration and TFP. Conversely, the most consistent finding of this study is a negative association between migration intensity and capital intensity, suggesting that migration shocks are partially absorbed through a slower adjustment of capital relative to labour, while labour and capital productivity show more mixed and less precise estimates.

Thus, these findings indicate that the consequences of migration for productivity depend fundamentally on the speed and institutional capacity for capital and organizational adjustment, rather than operating through a single, uniform channel. Therefore, this dissertation concludes with a discussion of the policy implications of this distinction and the need to combine migration policy with investment in complementary capital.

KEYWORDS: Migration; Total Factor Productivity; Capital Intensity; Productivity Decomposition; European Union; Panel Data

JEL CODES: C23; D24; E22; F22; J61; O47.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Across advanced economies, weak productivity growth has become the main obstacle to long-term income growth, and Draghi's report (2024), commissioned by the European Commission, makes this point clear by warning that Europe is facing a structural decline in productivity, exacerbated by demographic constraints and growing global competition. Consequently, it is becoming increasingly urgent to strengthen the internal drivers capable of boosting productivity in Europe. In addition, the international mobility of workers, especially skilled ones, emerges as one of the key mechanisms capable of revitalizing the productive and innovative capacity of European economies. In this way, in the European political debate, migration is often presented as a demographic "solution" to the aging workforce - a tool for stabilizing the labour supply and the fiscal base. Migration does not merely represent a quantitative shock to the labour force. This phenomenon can also affect the efficiency with which economies combine capital, labour, and knowledge. Consequently, whether migration flows increase or decrease productivity is not a secondary issue - it is fundamental to assessing the consequences of mobility within and into the European Union in terms of growth. As a result, the question that arises is: when new workers arrive, what truly happens? Do receiving economies become more efficient, or do they simply reorganize the use of capital and labour?

Theoretically, the sign is ambiguous because the mechanisms can work in various directions. On the one hand, migration flows can increase productive efficiency through task complementarities, innovation, and also occupational reallocation. For example, when migrants and natives differ in comparative advantage, labour markets eventually can reorganise toward better task matching and raising efficiency even if wages do not change much (Peri & Sparber, 2009). Furthermore, migration can also boost productivity by expanding the generation and diffusion of ideas - especially when flows are skill-intensive - through innovation, patenting, and knowledge spillovers (Hunt & Gauthier-Loiselle, 2010; Kerr & Lincoln, 2010; Peri et al., 2015). More broadly, diversity in places of birth may boost economic performance by increasing the variety of skills and perspectives available to firms and regions, reflecting effects that appear to be stronger for skilled migration in wealthier economies (Alesina et al., 2016; Ottaviano & Peri, 2006).

At the same time, there are clear reasons why migration flows may reduce measured productivity, at least over relevant time horizons. Rapid inflows can create transitory frictions, like imperfect recognition credentials, mismatches, congestion of public services, and slower assimilation into high-productivity sectors, that lead to a reduction in output per worker, even if long-term effects are positive. A good illustration of this is the study by Borjas & Doran (2012), which shows that highly skilled migration can have specific negative effects, particularly in highly specialized contexts. In this specific case, the influx of Soviet mathematicians shortly after the collapse of the USSR significantly reduced the productivity of American researchers most exposed to direct competition, showing that, although such inflows can generate positive effects, the impacts on the receiving country can initially be considerable and contradictory.

Another consideration to have in mind is the one presented in Peri (2012), related to capital adjustment: if the labour force expands faster than the capital stock, as a result, capital-labour intensity may decline, so labour productivity may fall even when underlying efficiency (TFP) remains unchanged. Given that, this happens not because workers have become less efficient, but because the capital-labour ratio has changed. On the other hand, Lewis (2011) shows that firms do not simply absorb this adjustment in a passive way; they actively respond by altering their technology and capital choices according to the relative supply of skills available. Nevertheless, if migrants initially concentrate in low-capital-intensive sectors, changes in composition can mechanically alter aggregate labour productivity without reflecting technological progress. These are not "second-order" complications, but rather the reason why a productivity-focused analysis cannot be limited to a single key measure.

Thus, this paper argues that the proper way to address these competing narratives is to examine where migration manifests itself on the production side of the economy. Instead of treating "productivity" as a single outcome, this analysis distinguishes between total factor productivity, capital productivity, labour productivity, and capital intensity, four variables that behave differently when migration operates through technology adoption, organizational change, factor deepening, or sectoral reallocation. TFP reflects the residual measure of overall economic efficiency, which captures the effects generated by technology and innovation. Labour productivity and capital productivity are related to, but distinct from, TFP: labour productivity reflects how much output each worker produces, embedding both efficiency and the amount of capital each worker has available, while capital productivity reveals how intensively the existing capital stock is used. Finally, regarding capital intensity, this one represents the factor intensity ratio, measuring the amount of physical capital available for each worker to operate. Thus, the distinction is empirically important because the same migration shock can raise TFP, reflecting better matching, innovation, and, at the same time, decrease labour productivity through insufficient capital adjustment, or vice versa.

Moreover, some macroeconomic evidence already suggests that migration can increase productivity in ways not captured by wage-centered assessments. By using variation across U.S. states, Peri (2012) finds that immigration is associated with higher productivity, consistent with channels that go beyond simple labour-supply effects. At the microeconomic level, firm-level studies like Mitaritonna et al. (2017) document productivity gains linked to shocks in the supply of immigrant labour, along with greater capital accumulation and improved export performance, indicating mechanisms that operate through firm modernization rather than pure substitution.

The European context is particularly instructive for this issue, as it combines deep economic integration with marked institutional heterogeneity across countries. The same migration flow - whether driven by free movement, EU enlargement, or humanitarian shocks - enters labour markets with very different contexts like employment protection regimes, wage-setting institutions, and barriers to occupational mobility. Evidence from Europe reveals that institutions have the capacity to shape how labour markets absorb immigrant inflows and how natives reallocate themselves across tasks and jobs. The pre- and post-crisis European experience analyzed by D'Amuri & Peri (2014), highlights adjustment through occupational and employment channels, rather than a single, uniform wage response. Meanwhile, quasi-experimental openings of labour markets to cross-border workers have demonstrated increased firm performance and innovation in neighbouring regions, also underscoring that mobility can function through firm modernization and local entrepreneurial dynamism, and not merely through labour supply (Beerli et al., 2021).

Thus, the principal objective of this paper is to examine the response of TFP, labour, and capital productivity and capital intensity to the changes in the labour force induced by the migration flows. Consequently, to address this, I build a country-year panel for the

European Economies by using the publicly available data from Eurostat and AMECO. The empirical strategy to be used will be a fixed-effects panel model, since this allows us to account for variations in productivity outcomes relative to the intensity of migration within countries over time (Wooldridge, 2010) while also allowing us to account for potential persistent differences between countries and shocks over the years. In summary, a fixed-effects panel model represents the best option since, through country fixed effects, we can clearly identify the effect of immigration by comparing each country with itself over time, while simultaneously eliminating any type of fixed heterogeneity related to differences in institutions, culture, geography, and productive structure across countries, a strategy widely used in the empirical literature, including Ortega & Peri (2014). Through year fixed effects, it is possible to remove common global shocks, such as the 2008 crisis and the COVID-19 pandemic. Thus, these effects ensure that the immigration coefficient is estimated not only by avoiding these two errors but also by contributing to a clear, credible analysis that is not biased by them.

In short, this article aims to contribute to the literature in three ways. First, it provides an explicit assessment of migration from a production perspective by estimating the impact of migration flows on TFP, capital productivity, labour productivity, and capital intensity, allowing the data to reveal whether migration operates primarily through efficiency gains or through factor deepening and changes in the composition of the labour force. Second, this study places the EU at the center of the analysis by addressing the gap in the literature regarding how migration shocks interact with the EU's particular combination of deep economic integration and institutional heterogeneity. Finally, this research also offers a methodological contribution by employing a robust fixed-effects panel model for 27 countries. This contrasts with studies such as Card (2001), which rely on shift-share instrument methods that may be less suitable for national-level panels. Thus, by using within-country variation over time to account for unobserved heterogeneity and global shocks (Wooldridge, 2010), this strategy provides clear evidence that challenges simplistic narratives regarding automatic efficiency gains.

Thus, regarding the organizational structure of this dissertation, it begins with Section 2.1, which presents a review of the literature that supports the research presented in this paper. Section 2.2 introduces the Theoretical Framework, which serves as the foundation for the construction of the model. Section 2.3 presents the Data, where, in addition to describing the variables used and their sources, I include figures that illustrate and support some of the study's conclusions. Section 2.4 outlines the Empirical Strategy, describing the estimation methods adopted and the rationale behind their selection. Section 2.5 presents the Empirical Analysis, where the results of the estimated regressions are reported and discussed, including both the preferred estimation method and the robustness tests and finally, Section 3 concludes the study.

2. MIGRATION AND PRODUCTIVITY: THEORY AND EVIDENCE

2.1. LITERATURE REVIEW

Given the significant increase in the free movement of people, it is important to study the impact of this movement on the productivity of host countries. Consequently, the relationship between immigration and productivity has been extensively studied over the years by various authors. In this regard, Jorgenson & Griliches (1967) provide a good starting point for this section, as they demonstrated that productivity growth depends crucially on how we measure capital and labour, emphasizing that empirical analysis is only credible when it is based on sound methodological foundations. Similarly, decades later, Syverson (2011) reinforces this perspective by showing that differences in the productivity of firms and economies arise not only from available technology, but also from how it is combined with other factors that impact internal organization, the quality of human capital, and reallocation.

The classical literature has been built around the relationship between international migration and productivity, highlighting three main mechanisms: innovation and the diffusion of knowledge, task specialization and factor complementarities, and, finally, market-wide reallocation and regional diversity externalities. As a result, this literature review is organized as follows: first, I discuss the impact of these three mechanisms; second, I will contextualize the impact of migration at the micro and macro levels; third, I will present what the literature indicates regarding the mechanisms of this relationship; and finally, I will provide a summary highlighting some gaps that this paper aims to address.

In the field of innovation, studies such as Niebuhr (2010), Østergaard et al. (2011), and Ozgen et al. (2011) emphasize that the cultural and cognitive diversity of workers increases the likelihood of incremental and radical innovation in companies, concluding that diverse teams, in addition to expanding the scope of technological demand, have a positive impact within companies. Alongside innovation, the generation of new ideas also stands out as one of the main links between migration and productivity, as reflected in the paper by Hunt & Gauthier-Loiselle (2010), which demonstrates that the presence of highly skilled immigrants increases the number of patents at a rate twice that of natives, concluding, numerically, that a 1 percentage point increase in the proportion of highly skilled immigrants raises the number of patents per capita by 9 to 18%. In the same context, Kerr & Lincoln (2010) analysed the impact that the increase in H-1B visa approvals had on employment, and the number of patents held by immigrants in SE fields (Science and Engineering), both in the cities and in the companies analysed. Similarly, the study by Peri et al. (2015) shows that the presence of foreign STEM (Science, Technology, Engineering, and Mathematics) workers also contributes positively to GDP growth and wage increases in American cities. Overall, this collection of literature helps to establish a link between skilled migration and innovation and the dissemination of ideas by demonstrating that the latter plays a central role in boosting productivity, both through the direct generation of knowledge and through its dissemination among diverse teams.

In the context of task specialization, recent literature emphasizes that immigration can alter not only the composition of the workforce but also the internal organization of firms and their allocation of tasks. An example of this is the study by D'Amuri & Peri (2014) and Foged & Peri (2016), which demonstrates how firms and native workers react to the entry of immigrants into the labour market. They concluded that what is occurring is a shift of native workers toward more communication-intensive tasks and of immigrants toward more manual tasks, thereby contributing to increased aggregate efficiency. On the capital side, Lewis (2011) demonstrates that when the supply of less-skilled labour from immigration increases, American factories tend to adopt less automation per unit of production, replacing only those machines that complement skilled labour. Lewis's finding is consistent with Peri's (2012) observation, which shows that immigration can increase TFP while reducing technological bias and decreasing, although slightly, capital intensity. Finally, concerning the general equilibrium, the work by Ottaviano & Peri (2012) highlights that imperfect substitutability between immigrants and natives implies only small effects on average wages and potential productivity gains, noting that even in labour markets with high inflows of immigrants, the task structure adjusts, minimizing competition between groups and reinforcing complementarity among workers.

Taken together, this literature demonstrates that immigration can influence labour productivity through multiple interconnected channels, whether via task adjustments, internal reorganization of firms, endogenous technological choices, or complementarity of skills.

Finally, through market-wide reallocation and regional diversity externalities, the geographical and urban literature has helped to corroborate the positive effect of diversity on productivity. This is reflected in the paper by Bellini et al. (2013), which stands out as one of the most relevant studies in demonstrating a positive relationship between cultural diversity and productivity at the regional level. Following the approach of Ottaviano & Peri (2006), but adapted to Europe, the study concludes that more diverse regions tend to produce more efficiently, and it has also been found that this diversity contributes to improving the economic performance of the European regions analysed. Nathan & Lee (2013) and Nathan (2016), while both arguing that cultural diversity can generate economic advantages for companies, differ in how they make this case. The first stands out for defending a more optimistic view by arguing that more diverse teams tend to innovate more and stimulate entrepreneurship, especially if this diversity occurs in multicultural contexts. Nathan (2016), on the other hand, explores this topic from a more cautious perspective, arguing that diversity can generate these positive effects, but not in a linear form, as these effects depend on the contexts in which they occur, such as the urban context, the type of company, and the sector of activity. Finally, Ottaviano & Peri (2006) also contribute to this field by examining whether increasing cultural diversity in American cities has an impact on the productivity and well-being of native-born residents. By studying data for the period between 1970 and 1990, they concluded that there is, in fact, a positive and economically significant correlation between greater cultural diversity, wages, and housing rents.

Thus, taken together, this literature highlights that the effects of immigration, in addition to not being uniform, depend on the capacity of the urban structure, economic density, and the ability of regions to transform diversity into productive efficiency, noting that regions with more effective institutions, flexible labour markets, and innovative ecosystems tend to transform diversity into productivity more easily.

Turning now to the macroeconomic evidence, at the aggregate level, early and influential evidence from the United States shows that immigration increases TFP without harming the employment of native-born workers (Peri, 2012). In a cross-country analysis, Ortega & Peri (2014), extend a geography-based gravity instrument, in the spirit of Frankel-Romer (1999), to estimate the causal effect of openness to trade and migration on per capita income. Their results reveal no robust effect found for trade openness, unlike immigration, which had a positive and statistically significant impact on countries' income, driven mainly by increases in TFP. Turning now to an OECD panel, Boubtane et al. (2016) use an SYS-GMM model to assess the positive effects of immigration on economic growth, concluding that immigrants' human capital contributes to increasing GDP per capita and that a permanent increase in migration flows raises GDP per worker. However, it is important to note that the authors reveal that the net growth effect remains relatively small, including in countries with highly selective migration policies. These results help reinforce the view that the macroeconomic effects of immigration are predominantly positive, even in different institutional contexts. The historical records also confirm the significant aggregate effects that European immigration during the Era of Mass Migration in the United States had on income, urbanization, and innovation in the long term, with short-term channels mediated by industrialization and agricultural productivity (Sequeira et al., 2020). Recent macroeconomic evidence also highlights that, even in contexts of large immigration inflows, labour market adjustment does not materialize through reductions in wages or employment of native workers, suggesting that immigration and native labour are not close substitutes in production (Card, 2005). Overall, the evidence reviewed suggests the conclusion that the macroeconomic effects of immigration materialize mainly through mechanisms of internal reorganization and technological adjustments, rather than through negative pressures on existing factors of production and native workers.

The micro-level literature presents mixed results but provides relevant information on where productivity gains occur. Some studies assume that the presence of foreign workers directly influences firm productivity, both through internal reorganization and through the introduction of new skills and perspectives. On the other hand, others argue that this influx may result in associated costs or losses. Using German establishment data with production function estimates, Trax et al. (2015) note that a higher share of foreign workers, whether at the firm or regional level, does not automatically increase productivity. However, cultural heterogeneity generates strong positive indirect effects, emphasizing that regional diversity is at least as important as internal diversity. Conversely, in Denmark, Parrotta et al. (2014) estimate both reduced-form and structural specifications and find that educational diversity yields mixed results, while ethnic diversity shows, on average, a negative correlation with measured productivity, possibly reflecting communication and integration-related costs, suggesting that internal heterogeneity can generate both complementarities and coordination costs. Complementing this analysis, Malchow-Møller et al. (2019) reveal that the influx of highly skilled professionals, measured as "foreign specialists," leads to increased productivity and exports among firms in Denmark, suggesting that selecting workers based on expertise and complementarities with the firms' existing structure is important for performance outcomes. Taken together, microeconomic studies suggest that productivity gains resulting from migration are most evident where firms' capabilities are better able to absorb diversity, such as in knowledge-intensive activities and in large urban ecosystems capable of transforming diversity into new productive combinations. Conversely, in other contexts, this diversity can generate costs or even have a negative impact on productivity.

With that in mind, we will now focus on empirical studies. Migrants are not randomly distributed across countries, and host economies do not all react in the same way to migrant inflows. So, given these and other constraints, measuring the impact of these flows becomes difficult. Some influential models address the issue through natural experiments, labour market comparisons, or the use of "shift-share" tools. The China-shock design by Autor et al. (2013) explores the initial exposure of U.S. regions to Chinese competition to identify causal effects. This is relevant because it illustrates how baseline exposure can be used to study heterogeneous local effects. Some recent methodological studies, such as Goldsmith-Pinkham et al. (2020), Borusyak et al. (2022), and Adão et al. (2019), demonstrate how demanding such designs are. The first contributes by demonstrating that the validity of Bartik's instruments depends on the exogeneity of the shares. The second reinterprets these designs as quasi-experiments, attributing identification to the exogeneity of aggregate shocks. Finally, Adão et al. (2019) show that conventional standard errors in shift-share designs can be misleading, proposing an alternative inference method, that further highlights how demanding these designs are. In the case of migration, the warning by Jaeger et al. (2018) is particularly relevant since persistent settlement patterns can mix the short-run effect of new inflows with the slower adjustment of earlier groups. Given all these challenges, this paper will adopt a more modest strategy based on fixed effects in a panel, since this allows us to control for all time-invariant unobserved heterogeneity (Wooldridge, 2010), as well as common shocks that countries face over time. By using this strategy, which is consistent with the broader macro-level migration literature that employs panel specification to account for unobserved heterogeneity (Boubtane et al., 2016; Ortega & Peri, 2014), the objective is to provide transparent evidence within countries and interpret the estimates through a decomposition of productivity.

Through this literature, we have gained a comprehensive understanding of the impact of migration on the employment of the resident population, on wages, and on occupational adaptation. In addition, we have also become more aware of the impact that migration can have on how firms cope with shocks, whether through innovation, task reallocation, diversity, or the adoption of technology. What is not yet entirely clear, especially in a European context, is how these effects are reflected in productivity accounts - that is, not only in TFP but also in capital and labour productivity. Thus, this article directly addresses this void by examining the impact of migration flows through the decomposition of productivity into four key components. Consequently, the central question we seek to answer is whether migration flows are associated with higher TFP, lower capital intensity, higher capital and labour productivity, or some combination of these outcomes. In conclusion, by providing a framework that can be rigorously tested and interpreted, this research aims to clarify the specific mechanisms through which European economies adjust to the influx of new workers.

2.2. Theoretical Framework

Now that we have introduced the topic and reviewed the literature on the subject, we are at the ideal point to construct our model. Based on an analysis of various studies, we can already assume that there is evidence that migration flows have an impact on productivity, innovation, and task reorganization. However, this article aims to go beyond that conclusion. The objective of this paper is not simply to determine whether productivity has risen or fallen, but rather to analyse the impact that this movement has on total factor productivity, capital productivity, labour productivity, and capital intensity. Thus, what we hope to gain from constructing this model is a much deeper analysis, as the relevant question will not be merely whether productivity increased or decreased, but rather which component of it changed, whether it be efficiency, capital intensity, or labour composition.

Thus, to structure this decomposition, we start with an aggregate Cobb-Douglas production function. I write the framework at the same country-year level used in the empirical strategy by considering a receiving country i in year *t*. Value added Y_{it} is produced with reproducible capital K_{it}, effective labour L_{it} and Hicks-neutral efficiency A_{it}. Thus, a simple way to organise the accounting is

$$Y_{it} = A_{it} K_{it}^{\alpha i} L_{it}^{1-\alpha i}, \qquad 0 < \alpha_i < 1 \tag{1}$$

where α_{it} is the capital share. Following the tradition of accounting decomposition of productivity (Jorgenson & Griliches, 1967), we rely on the use of a simple accounting tool. Its value lies in the fact that it allows us to separate efficiency from factor intensity, thereby showing why different measures of productivity can tell different stories. This approach is widely used to interpret variations in efficiency and misallocation, as in Syverson (2011).

When lower-case letters are used to denote the numbers, factor productivity is measured by

$$a_{it} = y_{it} - \alpha_i k_{it} - (1 - \alpha_i) l_{it} \tag{2}$$

This residual a_{it}, is the empirical measure that comes closest to efficiency, but it remains a residual and can vary due to technology, matching, utilization, measurement error, or changes in how inputs are recorded (Syverson, 2011). Following the tradition of Jorgenson & Griliches (1967), it is useful to consider TFP alongside labour productivity, capital productivity, and capital intensity rather than interpreting it in isolation, as this decomposition provides a more complete picture of productivity growth and helps prevent misleading conclusions based on a single measure of performance. The accounting identities are

$$y_{it} - l_{it} = a_{it} + \alpha_i(k_{it} - l_{it}) \tag{3}$$

$$y_{it} - k_{it} = a_{it} - (1 - \alpha_i)(k_{it} - l_{it}) \tag{4}$$

These two equations illustrate the main point of this thesis in its simplest form, by demonstrating that labour productivity and capital productivity are not pure measures of efficiency. However, before analysing them, it is necessary to understand why capital intensity was included in our model. The inclusion of capital intensity (K/L) is essential for understanding how migration affects the production structure, as it complements the analysis of TFP and labour and capital productivity. While TFP captures efficiency gains, capital intensity allows us to capture adjustments in the factor mix. In the literature review section, we had already seen evidence that migration shocks cause firms to adjust, whether in terms of task reorganization (Peri & Sparber, 2009), technological implementation, or investment (Lewis, 2011). Accordingly, observing capital intensity allows us to distinguish between efficiency and composition effects, since increases in labour productivity may simply result from an increase in capital per worker rather than genuine efficiency gains (Jorgenson & Griliches, 1967; Syverson, 2011). Thus, although capital intensity is not evaluated as a final outcome like productivity measures, it is pertinent to include this variable in the study since it proves to be a useful mechanism for understanding how the economy adjusts when migration occurs.

Thus, focusing now on the equations, labour productivity and capital productivity are not pure measures of efficiency, as both include TFP, but they respond oppositely to capital intensity. Following the growth accounting framework established by Jorgenson & Griliches (1967), consider a scenario where capital per worker decreases while the total factor productivity (TFP) remains unchanged; in this case, output per worker decreases, while output per unit of capital increases. In other words, a decline in labour productivity would not mean that the economy has become less efficient, but rather that the labour force has grown faster than the stock of capital with which it works. Thus, this distinction is fundamental to interpreting the results of this paper, as it allows us to separate the genuine effects of efficiency from the effects of capital composition when assessing the impact of migration on productivity.

Based on this description, we can thus describe the intensity of capital as the fourth term, which appears on the right-hand side of both identities, and it is defined as

$$ki_{it} = k_{it} - l_{it} \text{ in logs, } KI_{it} = \frac{K_{it}}{L_{it}} \text{ in levels} \tag{5}$$

Thus, as explained earlier, capital intensity is not in itself a measure of productivity, but rather a factor intensity ratio that allows us to obtain a complementary measure in this analysis. This is presented alongside the TFP, labour and capital productivity, precisely because, as equations (3) and (4) show, it is the term that distinguishes a change in efficiency from a change in the amount of capital each worker operates. Without this measure, any variation in labour or capital productivity could not be attributed to a specific channel, making it impossible to separate actual technological progress from simple factor reallocation. Thus, this represents a central distinction emphasized by Jorgenson & Griliches (1967) for the growth accounting tradition and by Syverson (2011) in the context of productivity measurement.

The empirical section estimates changes rather than levels, so the same logic can be written in first differences:

$$\Delta(y_{it} - l_{it}) = \Delta a_{it} + \alpha_i \Delta(k_{it} - l_{it}), \tag{6}$$

$$\Delta(y_{it} - k_{it}) = \Delta a_{it} - (1 - \alpha_i)\Delta(k_{it} - l_{it}) \tag{7}$$

It is precisely because neither of these measures of productivity is a pure measure of efficiency that the empirical analysis uses four different models. Following Jorgenson & Griliches (1967), this multi-model approach ensures that the data reveals whether migration operates through efficiency gains, factor deepening, or changes in the labour-capital mix.

Let Mig_{it} denote migration intensity, measured as immigration inflows relative to lagged population, employment or the working-age population. The empirical model estimates conditional panel associations of the form

$$\Delta z_{it} = \beta_z Mig_{it} + \mu_i + \tau_t + X'_{it}\gamma_z + \varepsilon_{it}^z, \tag{8}$$

In this specification, z represents one of the four productivity variables, and the coefficient β_z should not be interpreted as a structural parameter, but rather as an association within the country, adjusted for fixed effects and controls. In other words, β_Z

describes how productivity varies in years of higher migration intensity but does not represent the fundamental causal effect of migration on economic parameters. The other components of Equation (8), such as X', represent a vector of macroeconomic and demographic controls, while μ_i and τ_t capture, respectively, country and year fixed effects. It is also worth noting that, although differentiation eliminates time-invariant effects, the inclusion of fixed effects remains relevant for controlling for structural differences in dynamics, whether adjustments between countries or shocks common to all of them in a given year. This approach is thus consistent with the standard practice in the macro-level migration literature, where fixed effects specifications are employed to address unobserved heterogeneity and potential endogeneity concerns (Boubtane et al., 2016; Ortega & Peri, 2014; Wooldridge, 2010).

Finally, the identities derived from the Cobb-Douglas model imply internal relationships among the estimated coefficients for TFP, capital intensity, and labour and capital productivity. Following the analytical tradition of Jorgenson & Griliches (1967), these accounting identities thus provide a useful way to verify whether the estimates tell a coherent economic story. Let β_A be the coefficient from the TFP regression, and β_{KI} the coefficient from the capital-intensity regression. Then the labour-productivity and capital-productivity coefficients should roughly follow

$$\beta_{LP} \approx \beta_A + \alpha_i \beta_{KI} \tag{9}$$

$$\beta_{CP} \approx \beta_A - (1 - \alpha_i)\beta_{KI} \tag{10}$$

These equations are not expected to hold exactly, since capital shares differ across countries and the regressions include control variables and measurement choices. However, the coefficients also help capture the economic logic. For example, if migration intensity is associated with lower capital intensity, then $\beta_{KI} < 0$, thereby pulling labour productivity down and capital productivity up, even when measured TFP does not change. On the other hand, if migration intensity is associated with higher TFP, then $\beta_A > 0$, and the sign of labour productivity depends on whether that efficiency gain is large enough to offset any decline in capital per worker.

These equations make certain empirical patterns easier to interpret. Let's consider the following: if β_A is close to zero, $\beta_{KI} < 0$, $\beta_{LP} < 0$, and $\beta_{CP} > 0$, then the results are more consistent with a reduction in capital than with lower efficiency, following the capital adjustment mechanism identified by Peri (2012). Another case is: If $\beta_A > 0$ while $\beta_{KI} < 0$, efficiency gains from migration coexist with a decline in capital intensity, suggesting a slower adjustment of capital to the increased labour supply. If, however, $\beta_A > 0$, $\beta_{LP} > 0$, and $\beta_{KI} \geq 0$, the evidence points to a more favourable absorption process, in which migration is accompanied by a deepening of capital or a rapid organizational adjustment. Finally, if $\beta_A < 0$, the result requires a more cautious interpretation, as this outcome may reflect true adjustment costs, mismatch, cyclical utilization, measurement error, or omitted time-varying shocks.

The timing of these changes also plays an important role in the analysis. Labour can enter the economy more quickly than capital, infrastructure, housing, and organizational routines can adjust. For this very reason, lagged and dynamic panel specifications serve not only as robustness checks but also to better understand the mechanism under analysis. A contemporaneous fall in capital intensity, followed by weaker or positive lagged associations, would suggest gradual capital adjustment, a process that reflects the slow technological response of firms documented by Lewis (2011) and persistent adjustment dynamics warned by Jaeger et al. (2018). A lagged association with TFP, on the other hand, would fit with resulting mechanisms such as learning, matching, innovation, or organizational change. Finally, a persistent increase in capital productivity without a corresponding increase in TFP would, in this case, point to a more intensive use of existing capital.

To conclude this section, we can state that the framework is modest, since it does not assume that migrants are identical labour units, nor that capital adjustment is always instantaneous, nor does it make the fixed effects estimates causal by construction. What this model commits to doing is maintaining an honest interpretation by not interpreting the panel estimates as a simple, single verdict on whether migration increases productivity or not. By focusing on within-country variation and decomposing productivity into its component parts, this approach aligns with the standard practice in macro-level migration literature that I already mentioned (Ortega & Peri, 2014; Boubtane et al., 2016). Thus, ultimately, what we aim to answer is whether periods of intensive migration are associated with changes in TFP, labour productivity, capital productivity, and capital intensity, and whether these trends interact in a way that provides a plausible explanation for economic adjustment.

2.3. Data Section and Stylized Facts

In order to effectively analyse the central point of this dissertation, regarding the impact of migration on productivity in European Union countries, I will construct an econometric model capable of addressing this question. However, before constructing the model, it is necessary to determine which variables are most useful to include in it.

Thus, the empirical analysis is based on the country-year database compiled for this dissertation, where each observation is a country i in a calendar year t. Initially, I start with a complete framework of 27 European Union member states observed from 1995 to 2024.

First, this thesis uses data from two main statistical sources, namely AMECO and Eurostat, which enable the construction of a panel of European countries for the period from 1995 to 2024. The AMECO database, maintained by the European Union, is particularly relevant as it provides annual time series for macroeconomic variables that are fundamental to this study, including GDP at constant prices, employment, gross fixed capital formation, capital stock, real compensation per employee, the unemployment rate, capital and labour shares, and, of course, the key variable of this paper, total factor productivity. Eurostat, meanwhile, also contributes to the development of this model by providing detailed information on population, demographic characteristics, migration flows, and education levels, thereby making it possible to capture the dynamics of European migration movements. Thus, the integration of these two sources enables the construction of a relevant and appropriate panel to estimate the impact of migration on productivity, while simultaneously controlling for structural and cyclical factors.

Another important point to note is that the raw dataset should not be confused with the actual regression sample, since, although the panel framework covers the period from 1995 to 2024, the preferred fixed-effects estimates require that immigration, productivity measures, lagged macroeconomic controls, and the contemporary higher education share be overlapping (Wooldridge, 2010). Thus, by imposing these requirements, we observe a reduction in the estimated data, with the main estimation sample now comprising 668 country-years, 27 countries, and the period from 1998 to 2024. While the specification without controls uses 680 country-years, the specifications with lags and distributed lags are slightly smaller since they require additional migration lags, this being a necessary methodological requirement to separate short-term impacts from long-term adjustments, as argued by Jaeger et al. (2018). For this reason, each regression table thus presents its own sample, rather than treating the entire 1995–2024 period as the estimation period.

Next, I will specify which variables will be used in the model. First, we have the country, the calendar year, and the population as of 1 January, sourced from Eurostat under the heading *demo_pjan,* serving as identifiers and dimension denominators. Regarding total immigration and emigration flows, also from Eurostat, we have *migr_imm1ctz* and *migr_emi1ctz,* respectively, which represent some of the main variables in this study. Based on these series and the population, I also calculated net migration, the immigration rate per 1,000 lagged residents, and the net migration rate per 1,000 lagged inhabitants. Regarding macroeconomic variables, we have, from the AMECO database, GDP at constant prices (OVGD), gross fixed capital formation (OIGT), net capital stock (OKND), real compensation per employee (RWCDV), the unemployment rate (ZUTN), and the total factor productivity index (ZVGDF). Employment in terms of employed persons is also taken from AMECO, as are the capital and labour shares.

The key variable in our model, represented by TFP (ZVGDF) as I mentioned earlier, comes from AMECO and directly describes the index values of total factor productivity. With regard to labour and capital productivity, since these are not directly available for analysis, both were calculated separately. Labour productivity was obtained by dividing real GDP by total employment, allowing this ratio to capture average efficiency per worker. Capital productivity, on the other hand, was calculated using the ratio of real GDP to net capital stock, thereby reflecting the efficiency with which physical capital is utilized. Together, these two measures not only complement TFP but also allow us to analyse whether the effects of migration are concentrated in a specific factor or whether, in general, they result in an efficient improvement in the production process. Additionally, capital intensity was calculated, which is obtained by dividing net capital stock by employment. Regarding the aggregates from Eurostat's labour force survey, these provide the percentage of the working-age population with less than primary, upper secondary, and tertiary education, and these educational attainment percentages will be used in our model as a contemporaneous control in the baseline specification.

With regard to the descriptive variable for migration, the measure to be used is the immigration rate per 1,000 inhabitants in the previous period. Following the methodology established by Boubtane et al. (2016), this empirical strategy follows the same underlying principle by weighting total immigration flows by the size of the host economy in the previous period, thereby making the migration shock comparable across countries of very different sizes.

As we know, exposure to migration is far from uniform across the European Union. The available data show that the average immigration rate is 10.6 immigrants per 1,000 inhabitants, but the range is wide, with the 10th percentile at 2.0 and the 90th percentile at 22.0. From this analysis of the figure, we can conclude that at the top of the distribution, with the highest average immigration rates, small and highly open economies such as Luxembourg, Malta, Cyprus, Ireland, Spain, Austria, and Belgium stand out. Conversely, Slovakia, Poland, Bulgaria, Latvia, Portugal, France, and Finland are among the countries with the lowest exposure. However, this dispersion is not a technical issue; it is part of the context in which a given number of migrants represents a very different impact in Luxembourg than in Germany, France, or Italy. As noted by D'Amuri and Peri (2014) for Western Europe, the degree to which migration translates into labour market outcomes depends critically on the flexibility of national employment protection regimes, suggesting that institutional context mediates the economic impact of migration flows.

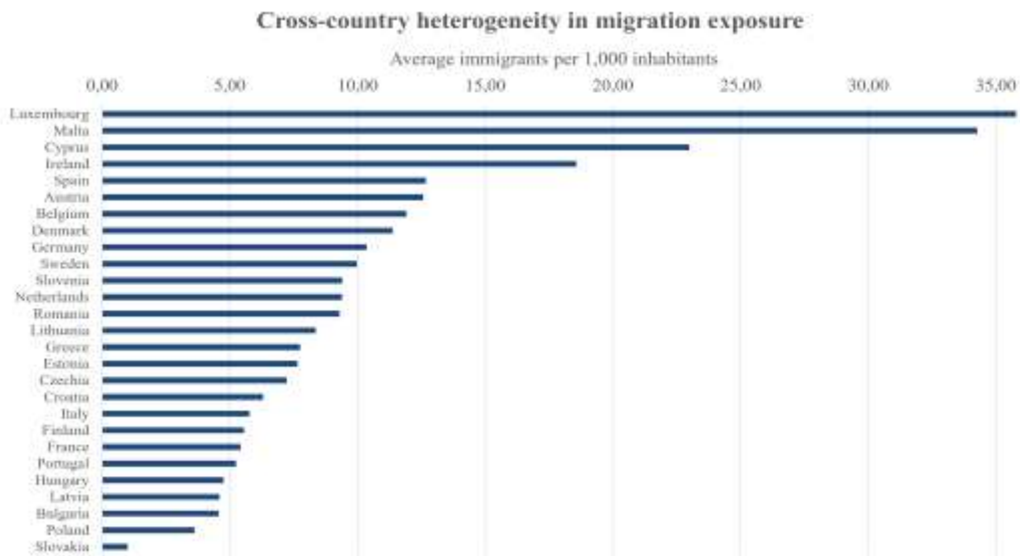

Figure 1: Cross-Country Heterogeneity in Migration Exposure

In addition, another relevant factor is the temporal pattern. First, we can conclude that the lowest average immigration rate was observed in the first decade of the 2000s, standing at less than 9 immigrants per 1,000 inhabitants in the countries that reported immigration data for this period. Following the global financial crisis, the rate increased, reaching 14.1 in 2019. However, a decrease due to the pandemic was followed by a gradual recovery in 2021 and a sharp increase from 2022 onwards. It is important to note that the periods between this year and 2024 recorded the three highest averages in the database (21.1, 18.5 and 16.9, respectively), along with a substantially greater dispersion between countries.

Thus, based on these analyses, we can conclude that the panel data reveal both persistent differences between countries and common patterns across Europe. As a result, the empirical strategy employs fixed effects, both by country and by year, in order to account for these differences (Wooldridge, 2010).

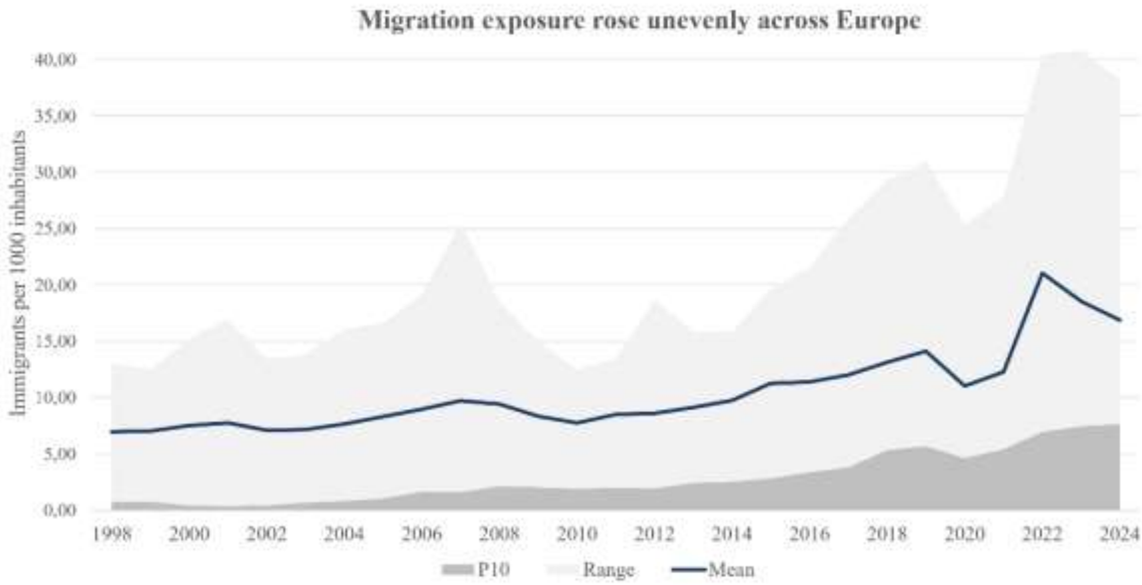

Figure 2: Migration Intensity over time

Table 1 presents summary statistics for the main variables used in the descriptive and empirical analysis. At this point, it is worth drawing several key insights from the data before moving on to the regressions. The first fact is that immigration is not a uniform European phenomenon, as there is significant variation not only between countries but also in meaningful shifts within them over time. This heterogeneity is visible directly in the data, with an overall standard deviation of the immigration rate of 10.0 immigrants per 1,000 inhabitants. Consequently, the panel data exhibits sufficient temporal variation to support a fixed-effects approach, consistent with the econometric principles of Wooldridge (2010), making it clear why permanent differences between countries should not be confused with the migration effect, a strategy that aligns with the standard practice for macro-level panels established by Ortega & Peri (2014) and Boubtane et al. (2016).

Table 1: Summary Statistics for Main Analytical Variables

Variable	Obs	Mean	Std.dev	Min	Max
Panel A. Migration and demographic variables					
Immigration rate per 1,000 inhabitants	680	10.60	10.0	0.02	77.92
Emigration rate per 1,000 inhabitants	674	7.11	5.83	0.11	41.56
Net migration rate per 1,000 inhabitants	671	3.46	6.79	-24.81	43.06
Population growth (%)	781	0.23	0.89	-4.60	4.34
Unemployment rate (%)	803	8.60	4.25	2.00	27.80
Panel B. Productivity and macroeconomic variables					
AMECO TFP growth (%)	783	1.23	2.69	-13.57	19.74
Labour productivity growth (%)	783	1.64	3.06	-12.10	18.57
Capital productivity growth (%)	783	0.02	3.46	-18.98	21.02
Capital intensity growth (%)	783	1.61	2.55	-8.02	16.98
Real GDP growth (%)	783	2.48	3.70	-17.48	22.01
Investment rate (%)	810	21.11	3.85	2.52	53.09
Real compensation growth (%)	783	1.59	3.30	-20.61	26.06
Panel C. Education shares of the working-age population					
Below upper secondary, ISCED 0-2 (%)	759	29.74	13.97	10.80	80.70
Upper secondary, ISCED 3-4 (%)	759	46.57	12.88	12.30	72.20
Tertiary, ISCED 5-8 (%)	759	23.69	9.10	4.90	48.30

Notes: Statistics are computed from the country-year workbook constructed from Eurostat migration and demographic series and the AMECO macroeconomic database. Growth rates are annual log changes multiplied by 100. Rates per 1,000 lagged inhabitants use the previous-year population as the denominator and the number of observations differs across variables because source coverage is not identical across countries and years.

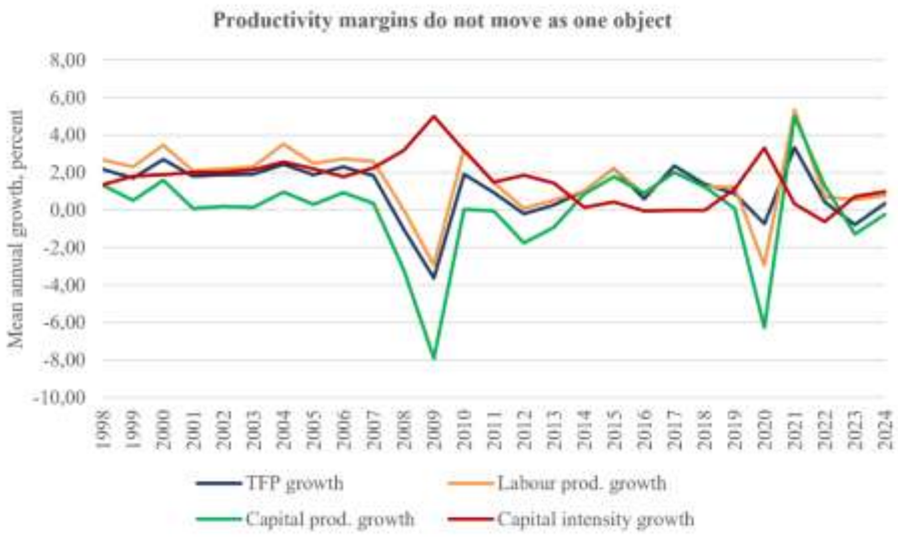

Figure 3: Productivity Margins in the Common Decomposition Sample

The second point that Figure 3 suggests is that productivity indicators do not evolve in the same way. In this regard, we can see that the dispersion, particularly between capital productivity and TFP, is significant. As Jorgenson & Griliches (1967) established, a rigorous explanation of productivity change requires accounting for the separate contributions of capital inputs and efficiency. An example of this is that a year of weak labour productivity growth may therefore be associated with lower efficiency, slower capital deepening, cyclical utilization, or a combination of these factors. This example is one of the practical reasons for estimating separate equations for the four measures, rather than treating productivity as an undifferentiated and isolated outcome (Syverson, 2011).

To conclude this section, we can note that these data, taken together, provide a useful but cautious empirical basis. Europe exhibits sufficient variation in migration exposure to raise the question of whether years with higher migration intensity differ from other years even within the same country. At the same time, the descriptive evidence cannot support a simple narrative that migration, automatically on its own, increases or decreases productivity. As a result, the best question is therefore more specific, namely: when migration intensity increases, does measured efficiency change, does capital per worker decrease, does output per unit of capital increase, or do these measures adjust together?

2.4. Empirical Strategy

After establishing the theoretical frameworks that will guide us throughout the paper, the objective of this section is to describe how the relationship between migration and productivity is tested empirically. In summary, in this section I will specify the econometric model, the variables used, and the estimation choices that will ensure the consistency and robustness of the results.

According to Wooldridge (2010), a fixed-effects model represents a panel specification that includes unit-specific intercepts, which capture unobserved and time-invariant heterogeneity, thereby enabling the identification of relationships based on variation within the unit over time. In our specific model, we will use fixed effects by country-year, whereby the former allows us to compare each economy with its own history, while the fixed effects by year eliminate shocks shared among countries in a given year. Thus, given the complexities of identifying a perfect natural experiment in a national-level panel, the resulting estimates are interpreted as carefully controlled associations rather than definitive causal effects, a cautious approach to inference consistent with the identification challenges discussed by Jaeger et al. (2018), in the context of aggregate migration panels.

Let i , denote the index representing the countries used in the model and t, denote the years. For each productivity object $q \in$ {TFP, LP, CP and KI}, y_{it}^{q} denotes the corresponding algorithm outcome. As previously explained, total factor productivity is obtained directly from the AMECO database. Labour productivity represents value added per worker, while capital productivity represents value added per unit of capital. Finally, capital intensity is defined as capital per worker.

The dependent variable is the annual change in the log outcome, which is defined as:

$$\Delta y_{it}^{q} = y_{it}^{q} - y_{i,t-1}^{q} \tag{11}$$

The use of changes helps to keep the focus on productivity growth rather than on permanent differences in productivity levels. This detail highlights an important point to bear in mind, given that, in Europe, countries persistently differ in terms of institutions, capital deepening, education, innovation systems, and migration policies. In addition, the use of fixed effects by country already accounts for differences that remain constant over time. However, expressing the results as rates makes the comparison more intuitive. Thus, the question is whether productivity growth changes when the intensity of migration changes within a country.

With regard to the intensity of migration, which is the main explanatory variable in the model, this is calculated as the ratio of immigration flows to the lagged size of the host economy:

$$Mig_{it} = \frac{Immigration_{it}}{Population_{i,t-1}}. \tag{12}$$

The baseline measure uses total immigration flows. However, to ensure a more comprehensive understanding of migration, I also analyse net migration, which nets out emigration, and a one-year-lagged version of migration intensity. Regarding the denominator, by using the lagged population weighting, the coefficient not only becomes comparable across countries of very different sizes but also avoids using the population response from the same year in the denominator.

The specification I will use as a reference is:

$$\Delta y_{it}^{q} = \beta_q Mig_{it} + \mu_i + \tau_t + X'_{it}\gamma_q + \varepsilon_{it}^{q} \tag{13}$$

Country-specific fixed effects μ_i, allow for the absorption of stable national differences, such as geography, long-term institutions, persistent productivity disparities, and, finally, historically different migration patterns. Fixed effects by year τ_t, on the other hand, account for shocks that affect European countries simultaneously, including events such as global recessions, episodes of energy price volatility, financial crises, EU-level policy changes, and the most recent COVID-19 period. In the implementation used here, X_{it} it includes lagged real GDP growth, the lagged investment rate, lagged population growth, the lagged real compensation growth, the lagged unemployment rate, and the contemporaneous percentage of people with higher education in the working-age population. The first three control variables capture general macroeconomic conditions. The lagged unemployment rate captures the cyclical state of the labour market into which migrants arrive, ensuring that we do not confuse the effect of migration with the economic cycle. The percentage of the population with higher education, meanwhile, controls for the skill composition of the host economy, which the literature, such as Peri et al. (2015), highlights as a key mediator of migration's effects on technology adoption. Finally, the use of lags in the macroeconomic variables helps ensure that the regression is less likely to capture variables that respond to migration in the same year.

With regard to the interest coefficient, β_q . This demonstrates, after accounting for the effects of the country-year and the included control variables, how the productivity output q varies within a country in years with higher migration intensity, and depending on the result, this same coefficient has different economic implications. Regarding TFP, its results are closer to an efficiency relationship. As for labour and capital productivity, their results refer, respectively, to output per worker and output per unit of capital. Thus, we conclude that the same migration shock can be interpreted in four different ways, since these represent distinct productivity margins in and of themselves.

Regarding the interpretation of fixed effects, this is based on a strong condition defined by:

$$\mathrm{E}\left[\varepsilon_{it}^{q} \middle| Mig_{it}, \mu_i, \tau_t, X_{it}\right] = 0 \tag{14}$$

By imposing this exogeneity condition, we ensure that the error term is uncorrelated with migration, thereby avoiding simultaneity and bias due to omitted variables. In other words, this condition ensures that the coefficient can measure the actual impact of migration on productivity. That is, by imposing this condition, the model is constructed so that any variation in productivity not caused by migration is not confounded by it. However, even when this condition is imposed, it is susceptible to failure for various reasons. These include the case where migrants move to countries immediately before productivity improves, if governments adjust migration policy in response to labour shortages, or if unobserved reforms affect both migration and productivity (Jaeger et al., 2018; Wooldridge, 2010). Because of these possibilities, the use of strong causal language should be avoided in this study. Consequently, the estimates are informative and should be understood as carefully controlled associations.

Regarding concerns about simultaneity, I also propose a more staggered version of the model:

$$\Delta y_{it}^{q} = \beta_q Mig_{i,t-1} + \mu_i + \tau_t + X_{i,t-1}'\gamma_q + \varepsilon_{it}^{q}. \tag{15}$$

With this specification, we examine whether the intensity of migration in the previous year is associated with productivity growth in the current year. Although this specification is extremely useful, it does not resolve all endogeneity issues, since migration itself can be forward-looking, as highlighted by Jaeger et al. (2018). However, estimating this version helps separate same-year co-movement from lagged adjustment. Thus, this approach is particularly relevant for capital intensity, since investment and capital accumulation rarely adjust instantaneously (Lewis, 2011).

Additionally, I also allow the association to develop over the course of several years:

$$\Delta y_{it}^{q} = \sum_{h=0}^{H} \beta_{q,h} Mig_{i,t-h} + \mu_i + \tau_t + X_{it}'\gamma_q + \varepsilon_{it}^{q}. \tag{16}$$

Specifically, these coefficients indicate whether the relationship between migration and productivity is immediate or gradual. A short-term decline in capital intensity followed by a recovery would be consistent with a slow adjustment of capital. On the one hand, a delayed association with TFP would more naturally point to slower mechanisms, such as learning, task reorganization, matching, or innovation. On the other hand, if capital productivity increases without a comparable increase in TFP, the more cautious interpretation would be to assume that existing capital is being used more intensively, rather than instantly assuming that the economy has become more efficient.

Next, I will discuss robustness checks and their importance in revealing where the benchmark pattern is stable or fragile. First, I estimate the model with and without the control vector X_{it}, where the version without controls presents the intra-country relationship after controlling for country and year fixed effects, and the controlled version examines whether this relationship holds when observable macroeconomic conditions are considered. Next, I also estimate a cumulative distributed lag specification with current migration intensity, with a one-year lag and a two-year lag. Finally, I add country-specific linear trends:

$$\Delta y_{it}^{q} = \beta_q Mig_{it} + \mu_i + \tau_t + \theta_i t + X_{it}'\gamma_q + \varepsilon_{it}^{q}, \tag{17}$$

Where, $\theta_i t,$ allows each country to follow its own smooth productivity trend. This is an intentionally strict specification, as it eliminates slowly evolving national productivity trajectories that might otherwise be mistaken for the effects of migration, a concern particularly relevant in panels where persistent patterns can confound short-run estimates (Jaeger et al., 2018). This makes it particularly useful in a European panel, since in this context productivity trajectories may differ for reasons that have little to do with migration.

Furthermore, I also present net migration as an alternative measure, since emigration also proves to be an important indicator of the relative labour supply in the host economy. When using total immigration, this measure encompasses intra-EU mobility, migration from non-EU countries, labour migration, family migration, and humanitarian flows. By using aggregated data that cannot account for these differences, I use the measures of immigration and net migration as summaries of the overall pressure on the labour supply, rather than as channel-specific instruments.

On the one hand, focusing now on the time frame in which the analysis takes place, we can assume from the outset that there are certain years that are too atypical to be excluded. Events such as the Great Recession, the sovereign debt crisis, the refugee flows of the mid-2010s, and the COVID-19 period can all affect both migration and productivity. For this reason, I present estimates that exclude these crisis periods.

The choice of weighting also plays an important role. In unweighted regressions, each country-year is assigned the same weight, whereas weighted regressions assign greater weight to larger countries, using the lagged population. These two estimates address slightly different questions. The first describes the average European country, while the second is closer to the experience of the average European resident. However, a credible model should not depend entirely on one of these choices.

For the inference, I pooled the standard errors at the country level, since both migration and productivity are likely to exhibit serial correlation within countries (Wooldridge, 2010). With 27 countries in the preferred sample, pooled standard errors are useful but should still be interpreted with caution. Consequently, in the analysis, I do not rely solely on statistical significance, as the sign, magnitude, and consistency of the four productivity responses are equally important for interpretation.

To conclude this section, we can thus emphasize that although a fixed-effects panel model could not resolve the identification problem surrounding migration, it can indeed organize the evidence in a disciplined manner. Its objective is therefore to show whether periods of intensive migration align with the productivity patterns described in the table, and whether these patterns are found in TFP, labour productivity, capital productivity, or capital intensity.

2.5. Empirical Analysis

After presenting the empirical strategy used, clarifying the model, and explaining the variables used and the theoretical framework, this section will focus on analysing the estimated results.

First, it should be noted that all regressions are performed using Stata, with standard errors aggregated at the country level. Regarding the preferred specification, it uses the common decomposition sample, which means that the four productivity outcomes are estimated based on the same 668 country-years and 27 countries. Regarding migration intensity, as mentioned earlier, this is measured as immigration flows per 1,000 lagged inhabitants. Thus, the coefficients can be interpreted as percentage-point changes in annual productivity growth associated with one additional immigrant per 1,000 inhabitants, after controlling for country and year fixed effects and lagged controls.

Table 2: Baseline Panel Fixed-Effects Estimates

	TFP	Labour productivity	Capital productivity	Capital intensity
Migration intensity	-0.015	-0.025	0.032	-0.057**
	(0.027)	(0.035)	(0.029)	(0.022)
Lagged real GDP growth	0.094	0.038	0.186***	-0.147***
	(0.057)	(0.051)	(0.049)	(0.025)
Lagged investment rate	0.020	0.060	-0.138	0.198***
	(0.110)	(0.104)	(0.149)	(0.056)
Lagged population growth	-0.343**	-0.300*	-0.576**	0.276
	(0.165)	(0.166)	(0.241)	(0.177)
Lagged unemployment rate	0.111**	0.088*	0.162**	-0.074*
	(0.044)	(0.047)	(0.058)	(0.036)
Lagged real compensation growth	0.091*	0.104**	0.014	0.091
	(0.047)	(0.050)	(0.060)	(0.064)
Tertiary education share	-0.016	-0.014	0.006	-0.020
	(0.041)	(0.040)	(0.059)	(0.054)
Observations	668	668	668	668
Countries	27	27	27	27
Within R^2	0.062	0.045	0.130	0.176
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are annual log changes multiplied by 100. Migration intensity is total immigration inflows per 1,000 lagged inhabitants. Control variables are lagged one year and include real GDP growth, the investment rate, population growth, the unemployment rate and real compensation growth; the tertiary-education share is contemporaneous. Standard errors clustered by country are in parentheses. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table 2 presents the baseline fixed-effects panel model, from which we can determine the impact of migration intensity on our four dependent variables. First, upon analysing the relationship between migration intensity and TFP, the coefficient is negative, small, and statistically indistinguishable from zero. This result is important for immediately deducing that the data do not support the simplistic claim that immigration increases efficiency as measured in the short term, contrary to the positive associations documented by Peri (2012) and Ortega & Peri (2014) in other institutional and geographic contexts. As for the labour productivity coefficient, it is also negative and statistically insignificant, suggesting no clear association between migration intensity and labour productivity growth within European countries over this period. Concerning the capital productivity coefficient, although it is positive, at 0.032, it is likewise statistically insignificant once lagged controls and the tertiary education share are included, thus preventing any strong conclusion about this relationship. Meanwhile, the only statistically robust result is the capital intensity coefficient of -0.057, which is consistent with the capital adjustment mechanisms documented by Peri (2012) and Lewis (2011). Regarding the model quality, as reflected in the Within analysis, the Within R^2 ranges from 0.045 to

0.176, values that are modest but typical of macroeconomic panel models. As a result, the baseline specification points to a moderate version of the mechanism within the theoretical framework, since the strongest reference signal is not an efficiency gain, but rather the fact that years of higher migration intensity are associated with a decline in capital per worker.

In this specific specification, the coefficients associated with migration intensity are not statistically significant for TFP, labour productivity, and capital productivity. Thus, it is not possible to conclude that migration actually influences these variables. In contrast, capital intensity, which in this case can be interpreted differently, is statistically significant at the 5% level. In this case, an increase of 10 immigrants per 1,000 inhabitants is associated with a reduction of approximately 0.6 percentage points in the growth of capital intensity. However, despite this interpretation of the coefficients, it is important to bear in mind that the scale used of 10 migrants per 1,000 inhabitants serves only to illustrate the magnitude of the associations, and these results should be viewed with caution. Therefore, in summary, the objective of these results is indeed to describe conditional relationships, not causal effects of migration on productivity.

Regarding the control variables, according to Wooldridge (2010), their inclusion aims to isolate the effect of migration intensity on productivity by removing the influence of other macroeconomic and demographic factors that might otherwise bias the estimates. We will now analyse the control variables represented by lagged GDP growth, lagged investment rate, lagged population growth, lagged unemployment rate, lagged real wage growth, and finally, the proportion of the population with higher education. Overall, the results are aligned with standard economic theory, lending credibility to the model's specification. Firstly, regarding lagged GDP growth, this is positively associated with TFP and capital productivity, but negatively with capital intensity, revealing a pattern consistent with the growth accounting framework of Jorgenson & Griliches (1967), suggesting that during expansions, output grows faster than the capital stock per worker. The lagged investment rate demonstrates significant boosts in capital intensity, confirming the expected link between capital formation and the amount of capital available per worker.

The demographic and labour market controls also reveal important dynamics. On the one hand, lagged population growth exhibits significant negative effects on TFP and both labour and capital productivity, reflecting a dilution effect where a larger workforce shares the same technological and capital resources. On the other hand, the lagged unemployment rate shows positive associations with all three productivity measures (TFP, capital and labour productivity), consistent with a selection effect whereby firms retain the most productive workers during downturns, thereby raising average efficiency.

Finally, lagged real wage growth contributes positively to TFP and labour productivity, consistent with efficiency wage theory that higher wages attract quality workers and incentivize effort. Lastly, the share of higher education shows no significant impact, reflecting a result that can be explained by the fact that country fixed effects absorb much of the structural variation in human capital across countries. However, this analysis is surprising given the literature indicating that more skilled workers have a positive impact on productivity, as concluded in the paper by Peri et al. (2015).

Thus, to conclude the analysis of this table, we can note that the results of this fixed-effects panel specification show that macroeconomic control variables behave, for the most part, consistently with economic theory. Regarding the variable of interest, migration intensity does not reveal statistically significant effects on TFP, labour productivity, or capital productivity. The only robust effect is a negative association with capital intensity, suggesting that immigration may be associated with a relatively greater use of labour relative to capital, consistent with the capital adjustment mechanisms documented by Peri (2012) and Lewis (2011).

After analysing the preference equation, I also conducted robustness tests, which, according to Wooldridge (2010), are alternative estimates used to verify whether the results remain stable under alternative specifications. As a result, through the robustness tests, I will be able to verify whether or not the conclusions depend on specific model choices. The analysis follows below, and the tables can be found in the appendix.

The first example presents the model estimation without controls, considering only migration intensity and the fixed effects of country and year, thereby allowing an assessment of whether the inclusion of these variables substantially alters the coefficients of the variables of interest. The results point to a small negative response in capital intensity, while the other three variables do not yield precise estimates. Following the conclusion of the preferred estimation, the results show that migration intensity has no statistically significant effects on TFP, labour productivity, or capital productivity. Thus, the negative and significant effect on capital intensity remains, although this estimation yields a value of -0.028, lower than that of the baseline specification, and with a 5% significance level. Thus, the result suggests that the central conclusion of the analysis is robust to the exclusion of control variables, thereby reinforcing the credibility of the negative association between migration and capital intensity.

The second test uses migration intensity lagged by one period, a specification that allows us to address the potential issue that more productive countries may attract more immigrants during the same period. Thus, this lag helps resolve this issue by establishing a clearer temporal order between cause and effect. The results show a similar pattern to the previous test, indicating that lagged migration intensity has no statistically significant effects on TFP, labour productivity, and capital productivity. Consequently, capital intensity remains negative and statistically significant at -0.051, with a magnitude very close to that of the baseline specification, thus suggesting that the negative association between migration and capital intensity persists in this specification.

Next, the third test introduces a distributed lag model, including migration intensity and two additional lags, as well as an additional cumulative coefficient representing the sum of the previous three. Through this specification, this test allows the effect of migration to materialize gradually over time, rather than being confined to a single period, accounting for the slow technological and capital adjustment documented by Lewis (2011) and the persistent adjustment patterns highlighted by Jaeger et al. (2018). The results show that none of the individual coefficients, nor the cumulative coefficient, is statistically significant for TFP, labour productivity, capital productivity, or even capital intensity. The only exception is the first additional lag in labour productivity, which has a negative and statistically significant value of -0.051, suggesting that there is a negative effect with an additional lag of one period in this variable. Nevertheless, despite this exception, the cumulative effect on labour productivity is not significant, indicating that this impact does not accumulate persistently over time. Thus, taken together, these results suggest that the effects of migration on productivity are limited and not very persistent over time.

In addition, I also conducted a fourth and fifth test that present estimates weighted by country trend and population, respectively. The fourth test incorporates country-specific linear trends, reducing the risk of bias from omitted variables with a trending nature, a concern particularly relevant in panels where slowly evolving national trajectories may be mistaken for migration effects (Jaeger et al., 2018). The fifth test, meanwhile, uses population-weighted estimates, thereby allowing us to assess whether the results are influenced by the presence of small countries. Thus, by analysing both specifications, we can already conclude that migration intensity does not have statistically significant effects on TFP, labour productivity or capital productivity. Regarding capital intensity, the negative sign follows the trend and even increases in magnitude in both tests, thereby reinforcing the robustness of this association, with the fourth test yielding a significant coefficient of -0.082 at the 1% level, and the fifth yielding -0.079 significant at the 10% level . Another particularly interesting result is the emergence of negative and statistically significant coefficients in both tests, with special emphasis on the fourth, which reveals a negative association between higher education and TFP as well as labour and capital productivity. Thus, the situation described above may reflect measurement issues or issues regarding the composition of the skilled labour force not captured in the baseline specification, a pattern that contrasts with the positive effects documented by Peri et al. (2015).

Next, the sixth test excludes countries with an average population of less than 2 million inhabitants, reducing the sample from 27 to 23 countries and from 668 observations to 573 compared to the baseline specification. The objective is thus to determine whether the baseline results are influenced by small countries, whose labour market and productivity dynamics may differ substantially from larger economies, as suggested by evidence from small open economies in Europe (Beerli et al., 2021). In line with the previous tests, this estimate is consistent with the previous findings, since, once again, migration intensity does not have significant effects on TFP and labour and capital productivity. On the other hand, regarding the effect of migration intensity on capital intensity, not only does it remain consistent with what has been analysed so far, but its magnitude also increases, now representing the highest value in all robustness tests conducted to date.

Finally, we have the seventh and final robustness test, in which I excluded the years of economic crisis, specifically the periods 2008–2010, 2015–2016, and 2020–2021. The objective of this test is thus to assess whether the results of the specification are influenced by atypical dynamics associated with periods of severe economic contraction, during which both migration flows and productivity may behave exceptionally, as documented by D'Amuri & Peri (2014) for Western Europe. Thus, upon analysing the coefficients, we conclude that, even outside of crisis periods, migration intensity does not have statistically significant effects on TFP or labour productivity. As for capital intensity, the pattern repeats with the same magnitude as the baseline specification -0.057 and a 5% statistical significance, thus constituting a particularly strong confirmation of the robustness of this association. In a relevant finding, capital productivity also emerges in this specification with a positive and statistically significant effect, suggesting that, during periods of economic stability, migration may be associated with gains in capital productivity that are masked by the volatility characteristic of crisis years. A result consistent with the positive firm-level effects documented by Mitaritonna et al. (2017) in normal economic conditions. Finally, the considerable increase in the Within R^2 across all columns confirms that crisis years introduce substantial noise into the model, thereby hindering the identification of structural relationships between migration and productivity.

In summary, the seven robustness tests conducted confirm the stability of the results from the baseline specification. The central finding remains consistent across all specifications, indicating that migration intensity has no statistically significant effects on TFP, labour productivity, or capital productivity. On the other hand, the significant negative effect observed on capital intensity is the most robust result of the analysis, as it persists across six of the seven model specifications and ranges from -0.028 to -0.107, with the only exception being the distributed lag specification, where the coefficient is not statistically significant. Additionally, the only result worth noting beyond capital intensity is the positive effect on capital productivity in the estimates that exclude the crisis years, suggesting that during periods of economic stability, migration may be associated with gains in capital productivity. Therefore, given its limited robustness across other specifications, their interpretation should also be approached with caution.

Table 3: Alternative Migration Measure: Net Migration

	TFP	Labour productivity	Capital productivity	Capital intensity
Net migration	-0.044*	-0.057	0.033	-0.090***
	(0.025)	(0.036)	(0.029)	(0.027)
Lagged real GDP growth	0.103*	0.052	0.178***	-0.126***
	(0.056)	(0.051)	(0.046)	(0.025)
Lagged investment rate	0.025	0.067	-0.136	0.203***
	(0.108)	(0.103)	(0.146)	(0.052)
Lagged population growth	-0.318*	-0.267	-0.576**	0.309
	(0.161)	(0.166)	(0.256)	(0.198)
Lagged unemployment rate	0.096**	0.071*	0.173***	-0.102***
	(0.040)	(0.042)	(0.057)	(0.033)
Lagged real compensation growth	0.083*	0.095*	0.016	0.079
	(0.046)	(0.049)	(0.058)	(0.061)
Tertiary education share	-0.016	-0.015	0.013	-0.028
	(0.038)	(0.038)	(0.057)	(0.057)
Observations	660	660	660	660
Countries	27	27	27	27
Within R^2	0.070	0.056	0.130	0.196
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are annual log changes multiplied by 100. Net migration is (immigration minus emigration) per 1,000 lagged inhabitants. Control variables are lagged one year and include real GDP growth, the investment rate, population growth, the unemployment rate and real compensation growth; the tertiary-education share is contemporaneous. Standard errors clustered by country are in parentheses. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

In order to capture the demographic balance rather than gross flows, I replace the immigration rate with net migration, defined as the difference between immigration and emigration per 1,000 lagged residents. Through this substitution, I will be able to assess whether the results are sensitive to the definition of the variable of interest by distinguishing between the effect of total migration flows and the net effect on the resident population, a distinction explored in the cross-country literature by Ortega & Peri (2014). First, we can note that although there are some relevant differences, the results are generally consistent with those of the baseline specification. In this specification, net migration now has a negative and statistically significant effect on TFP, with a value of -0.044 and a 10% significance level, suggesting that higher net inflows may be associated with a lower TFP growth. This result may reflect some adjustment costs, compositional effects, or the possibility that gross immigration flows overstate productive contribution of migrants when return migration is accounted for. In keeping with the trend, capital intensity not only maintains a negative and statistically significant effect but also increases the magnitude of its coefficient -0.090, compared to the baseline specification -0.057, allowing this analysis to reinforce the robustness of this association regardless of the migration measure used. As for the effect on capital and labour productivity, both continue to show no statistical significance.

Taken together, these results suggest that the choice between gross and net migration does not alter the main conclusions of the primary analysis. Consequently, it does indicate that the net migration balance may capture additional effects on the labour force participation rate that gross immigration flows fail to identify, most likely because they also incorporate the dimension of emigration and its effects on the composition of the labour force (Docquier & Rapoport, 2012).

In summary, unlike studies such as Peri (2012) and Ortega & Peri (2014), this empirical analysis does not show that years of intensive migration have a positive and significant impact on TFP. Throughout the analysis of the tests conducted, the TFP coefficients generally exhibit small, unstable, or statistically weak values. However, the most consistent conclusions, in line with Lewis (2011) and Peri (2012), lie outside the TFP and are essentially reflected in capital intensity. Regarding capital productivity, it is positive in some specifications, especially after excluding the crisis years, however, not robust enough to constitute a main result. As for labour productivity, it weakens in several specifications, but without sufficient precision. Consequently, the evidence presented suggests that migration shocks are partially absorbed through adjustments in the capital-labour ratio, while the effects on TFP prove too slight to be accurately identified through an aggregate fixed-effects estimation, making it impossible, using this design, to draw conclusions about the impact of migration on aggregate productive efficiency.

3. CONCLUSION AND POLICY INTEGRATION

At the beginning of this work, it was noted that the term "productivity" is too broad to allow for a meaningful discussion of migration. Thus, based on the suggested literature, it was possible to determine that when new workers arrive, employment and production can expand before factors such as capital, infrastructure, and organizations have time to adjust (Lewis, 2011). In this sense, labour productivity may decline, even if the underlying efficiency of production has not actually decreased. Output per unit of capital, on the other hand, may also increase, and this increase does not need to be explained by the fact that the economy has suddenly become more advanced, but rather because the capital stock is being utilized more intensively. Thus, considering the situation described above, the focus of this thesis was on making these distinctions explicit by separating total factor productivity, labour productivity, capital productivity, and capital intensity, following the growth accounting tradition established by Jorgenson & Griliches (1967) and the productivity measurement framework of Syverson (2011), rather than examining this relationship by analysing only a single "productivity" coefficient.

Using a panel data model with fixed effects by country and year, covering 27 European Union member states over the estimation period from 1998 to 2024, we attempted to determine whether immigration acts as a driver of efficiency or whether it primarily results in a reallocation of capital-labour inputs. Upon analysing the results, the possible inferences lead to a cautious conclusion. Thus, in the panel of European countries used here, it was found that years of intensive migration are not associated with a robust increase in measured TFP, quite the contrary. The estimates of this productivity measure are small, unstable, or statistically weak, both in the preferred specifications and in the robustness tests. Conversely, the clearest and most robust signal is reflected in the capital intensity coefficient in the preferred estimates, revealing that higher migration intensity is associated with lower growth in capital intensity (coefficients ranging from -0.028 to -0.107). This result holds up to several important checks, including country-specific trends, population weighting, exclusion of small countries, and periods of crisis. Finally, regarding labour and capital productivity, the first often moves in the same direction, although less precisely. Meanwhile, capital productivity is positive in some specifications, especially outside of crisis periods, potentially indicating structural gains masked by economic volatility; however, it proves too sensitive to specification and sampling choices to support the argument on its own.

Thus, what I intend to draw from this study is not, therefore, the conclusion that migration reduces productivity. Rather, the most plausible interpretation of the results is that migration shocks are partially absorbed through a reduction in capital-labour ratios. Thus, when the labour supply expands more rapidly than the capital stock and the systems surrounding it cannot respond with the same speed, the economy can temporarily function with less capital per worker. In this sense, lower labour productivity does not necessarily translate into weaker or less efficient workers; it may simply mean that capital moves more slowly than the labour supply. Thus, taking this distinction into account is essential, since it shifts the political debate from the question of whether migration is harmful to what actually makes it productive (Beerli et al., 2021).

As far as policy is considered, the first lesson I take from analysing these results is that migration policy cannot be separated from investment policy. Let us consider this: if host economies attract additional workers but do not expand complementary capital, what we see is that short-term productivity gains may appear disappointing, even when migration increases total output and alleviates labour shortages- as the evidence from institutional contexts with limited absorptive capacity suggests (Beerli et al., 2021). Thus, complementary capital must be understood broadly, encompassing not only more machinery but also improvements in housing, transportation networks, schools, healthcare systems, digital infrastructure, technology, management capacity, and the administrative systems that help workers access jobs matching their skills. Thus, as documented by Lewis (2011) and D'Amuri & Peri (2014), the speed at which these systems adjust critically determines whether a migration shock translates into efficiency gains or simply into pressure on capital intensity, and the results of this thesis suggest that, in the European context, the latter tends to predominate in the short-term.

With regard to integration policy, in line with Peri & Sparber (2009), D'Amuri and Peri (2014) and Beerli et al. (2021), this analysis also demonstrates its importance in the productivity debate. Factors such as language training, the recognition of foreign qualifications, the alignment of job supply and demand, targeted training, and the streamlining of administrative procedures for migrants entering the country, influence how quickly new workers begin to perform productive tasks. The same influx of labour can have different consequences, depending on whether migrants are placed in roles suited to their skills, whether companies effectively reorganize tasks, and whether nationals and migrants complement each other in the tasks they perform, a mechanism documented by Peri & Sparber (2009) as a key source of efficiency gains. Thus, within the scope of this dissertation, a sound integration policy appears to be an effective way to transform a shock in the labour supply into an efficiency gain.

Thus, another important issue concerns the limitations. The fixed-effects panel design used in this study allows for the absorption of persistent differences between countries and common shocks over the years, but it does not make migration random. As a result, migrants may move to economies before productivity improves, policies may respond to labour shortages, and unobserved reforms may be able to affect both migration and productivity simultaneously. Similarly, the data used in the model are aggregated, so they cannot identify firm-level decisions, task reallocations, technological choices, or worker-level matches through which the mechanism operates. For this reason, and consistent with the inferential limits of fixed-effects designs (Wooldridge, 2010), the estimates should be interpreted as robust conditional associations at the country level, rather than definitive causal estimates.

One such approach could involve linking the aggregate breakdown to sector-level and firm-level evidence. First, using sector-level data, it might be possible to show whether capital reduction is concentrated in labour-intensive activities or sectors where capital adjustment is particularly slow, building on the sectoral evidence documented by Lewis (2011). Data at the firm level, on the other hand, could reveal how firms react when faced with the supply of migrant labour, that is, whether they expand employment without investing, adopt different technologies, or simply reorganize tasks and improve matching (Beerli et al., 2021; Mitaritonna et al., 2017; Peri & Sparber, 2009). Additionally, implementing a more robust causal design focused on using policy variations or historical settlement patterns, with careful attention to persistence problems highlighted by Jaeger et al. (2018), would also help to separate the effects of migration from selection in growing economies.

Finally, the broader message this study aims to highlight is that migration should not be assessed solely and exclusively through a single productivity statistic, but rather by decomposing it. As we have analysed throughout this study and the data used, the strongest evidence is not that migration increases TFP, nor that it harms economic efficiency. Rather, it is that host economies appear to absorb migration, in part, through the capital-labour ratio. Thus, if countries want migration to support productivity rather than merely expand the labour supply, they need to invest in institutions and infrastructure that allow capital, technology, and organizational capacity to move alongside the labour force. Thus, migration can indeed be part of a growth strategy, but it will only be successful if the rest of the economy is prepared to absorb it.

REFERENCES

Adão, R., Kolesár, M., & Morales, E. (2019). Shift-Share Designs: Theory and Inference*. *The Quarterly Journal of Economics, 134*(4), 1949–2010. https://doi.org/10.1093/qje/qjz025

Alesina, A., Harnoss, J., & Rapoport, H. (2016). Birthplace diversity and economic prosperity. *Journal of Economic Growth*, *21*(2), 101-138. https://doi.org/10.1007/s10887-016-9127-6

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, *103*(6), 2121–2168. https://doi.org/10.1257/aer.103.6.2121

Beerli, A., Ruffner, J., Siegenthaler, M., & Peri, G. (2021). The Abolition of Immigration Restrictions and the Performance of Firms and Workers: Evidence from Switzerland. *American Economic Review, 111*(3), 976–1012. https://doi.org/10.1257/aer.20181779

Bellini, E., Ottaviano, G. I. P., Pinelli, D., & Prarolo, G. (2013). Cultural Diversity and Economic Performance: Evidence from European Regions. *In* R. Crescenzi & M. Percoco (Eds.), *Geography, Institutions and Regional Economic Performance* (pp. 121-141). Springer. https://doi.org/10.1007/978-3-642-33395-8_7

Borjas, G. J., & Doran, K. B. (2012). The collapse of the Soviet Union and the Productivity of American Mathematicians*. *The Quarterly Journal of Economics*, *127*(3), 1143-1203. https://doi.org/10.1093/qje/qjs015

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-Experimental Shift-Share Research Designs. *The Review of Economic Studies, 89*(1), 181–213. https://doi.org/10.1093/restud/rdab030

Boubtane, E., Dumont, J.-C., & Rault, C. (2016). Immigration and economic growth in the OECD countries 1986-2006. *Oxford Economic Papers*, *68*(2), 340-360. https://doi.org/10.1093/oep/gpw001

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics*, *19*(1), 22–64. https://doi.org/10.1086/209979

Card, D. (2005). Is the New Immigration Really so Bad? *The Economic Journal*, *115*(507), F300-F323. https://doi.org/10.1111/j.1468-0297.2005.01037.x

D'Amuri, F., & Peri, G. (2014). Immigration, Jobs, and Employment Protection: Evidence from Europe before and during the Great Recession. *Journal of the European Economic Association,* *12*(2), 432–464. https://doi.org/10.1111/jeea.12040

Docquier, F., & Rapoport, H. (2012). Globalization, Brain Drain, and Development. *Journal of Economic Literature,* *50*(3), 681-730. https://doi.org/10.1257/jel.50.3.681

European Commission. (2024). The future of European competitiveness: A competitiveness strategy for Europe (Draghi report). European Commission. https://commission.europa.eu/topics/competitiveness/draghi-report_en

European Commission. (2026). AMECO database: GDP at constant prices (OVGD), Real compensation per employee (RWCDV), Unemployment rate (ZUTN), Net capital stock (OKND), TFP index (ZVGDF), Employment persons (NETD), Gross Fixed capital formation (OIGT), Capital share (ZVGDK), Labour share (ZVGDE). Directorate-General for Economic and Financial Affairs. https://economy-finance.ec.europa.eu/economic-research-and-databases/economic-databases/ameco-database_en

Eurostat. (2026). Population and migration statistics: Total immigration (migr_imm1ctz), Total emigration (migr_emi1ctz), Population on 1 January (demo_pjan), Population share with ISCED (less than upper secondary, upper/post-secondary non-tertiary, tertiary) (edat_lfse_03). European Commission. https://ec.europa.eu/eurostat/web/main/data/database

Foged, M., & Peri, G. (2016). Immigrants' Effect on Native Workers: New Analysis on Longitudinal Data. *American Economic Journal: Applied Economics, 8*(2), 1–34. https://doi.org/10.1257/app.20150114

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review, 110*(8), 2586–2624. https://doi.org/10.1257/aer.20181047

Hunt, J., & Gauthier-Loiselle, M. (2010). How Much Does Immigration Boost Innovation? *American Economic Journal: Macroeconomics, 2*(2), 31–56. https://doi.org/10.1257/mac.2.2.31

Jaeger, D. A., Ruist, J., & Stuhler, J. (2018). *Shift-Share Instruments and the Impact of Immigration* (Working Paper N. 24285). National Bureau of Economic Research. https://doi.org/10.3386/w24285

Jorgenson, D. W., & Griliches, Z. (1967). The Explanation of Productivity Change. *The Review of Economic Studies*, *34*(3), 249-283. https://doi.org/10.2307/2296675

Kerr, W. R., & Lincoln, W. F. (2010). The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention. *Journal of Labor Economics, 28*(3), 473–508. https://doi.org/10.1086/651934

Lewis, E. (2011). Immigration, Skill Mix, and Capital-Skill Complementarity. *The Quarterly Journal of Economics*, *126*(2), 1029-1069. https://doi.org/10.1093/qje/qjr011

Malchow-Møller, N., Munch, J. R., & Skaksen, J. R. (2019). Do Foreign Experts Increase the Productivity of Domestic Firms? *The Scandinavian Journal of Economics*, *121*(2), 517-546. https://doi.org/10.1111/sjoe.12286

Mitaritonna, C., Orefice, G., & Peri, G. (2017). Immigrants and firms' outcomes: Evidence from France. *European Economic Review, 96*, 62–82. https://doi.org/10.1016/j.euroecorev.2017.05.001

Nathan, M. (2016). Ethnic diversity and business performance: Which firms? Which cities? *Environment and Planning A: Economy and Space*, *48*(12), 2462-2483. https://doi.org/10.1177/0308518X16660085

Nathan, M., & Lee, N. (2013). Cultural Diversity, Innovation, and Entrepreneurship: Firm-level Evidence from London. *Economic Geography*, *89*. https://doi.org/10.1111/ecge.12016

Niebuhr, A. (2010). Migration and innovation: Does cultural diversity matter for regional R&D activity? *Papers in Regional Science*, *89*(3), 563–586. https://doi.org/10.1111/j.1435-5957.2009.00271.x

Ortega, F., & Peri, G. (2014). Openness and income: The roles of trade and migration. *Journal of International Economics*, *92*(2), 231-251. https://doi.org/10.1016/j.jinteco.2013.11.008

Østergaard, C. R., Timmermans, B., & Kristinsson, K. (2011). Does a different view create something new? The effect of employee diversity on innovation. *Research Policy, 40*(3), 500-509. https://doi.org/10.1016/j.respol.2010.11.004

Ottaviano, G. I. P., & Peri, G. (2006). The economic value of cultural diversity: Evidence from U.S. cities. *Journal of Economic Geography*, *6*(1), 9-44. https://doi.org/10.1093/jeg/lbi002

Ottaviano, G. I. P., & Peri, G. (2012). Rethinking the Effect of Immigration on Wages. *Journal of the European Economic Association*, *10*(1), 152-197. https://doi.org/10.1111/j.1542-4774.2011.01052.x

Ozgen, C., Nijkamp, P., & Poot, J. (2011). *Immigration and Innovation in European Regions* (SSRN Scholarly Paper N. 1908138). Social Science Research Network. https://doi.org/10.2139/ssrn.1908138

Parrotta, P., Pozzoli, D., & Pytlikova, M. (2014). Labor diversity and firm productivity. *European Economic Review, 66*, 144-179. https://doi.org/10.1016/j.euroecorev.2013.12.002

Peri, G. (2012). The Effect Of Immigration On Productivity: Evidence From U.S. States. *The Review of Economics and Statistics, 94*(1), 348-358. https://doi.org/10.1162/REST_a_00137

Peri, G., Shih, K., & Sparber, C. (2015). STEM Workers, H-1B Visas, and Productivity in U.S. Cities. *Journal of Labor Economics, 33*(S1), S225–S255. https://doi.org/10.1086/679061

Peri, G., & Sparber, C. (2009). Task Specialization, Immigration, and Wages. *American Economic Journal: Applied Economics, 1*(3), 135–169. https://doi.org/10.1257/app.1.3.135

Sequeira, S., Nunn, N., & Qian, N. (2020). Immigrants and the Making of America. *The Review of Economic Studies*, *87*(1), 382-419. https://doi.org/10.1093/restud/rdz003

Syverson, C. (2011). What Determines Productivity? *Journal of Economic Literature*, *49*(2), 326–365. https://doi.org/10.1257/jel.49.2.326

Trax, M., Brunow, S., & Südekum, J. (2015). Cultural diversity and plant-level productivity. *Regional Science and Urban Economics*, *53*, 85-96. https://doi.org/10.1016/j.regsciurbeco.2015.05.004

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2.ª ed.). MIT Press.

APPENDICES

Table A 1: Robustness: Fixed Effects without Controls

	TFP	**Labour productivity**	**Capital productivity**	**Capital intensity**
Migration intensity	-0.032	-0.036	-0.008	-0.028**
	(0.029)	(0.037)	(0.029)	(0.013)
Observations	680	680	680	680
Countries	27	27	27	27
Within R^2	0.007	0.008	0.000	0.007
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are annual log changes multiplied by 100. Standard errors clustered by country are in parentheses. This specification includes country and year fixed effects but no additional controls. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A 2: Robustness: Lagged Migration Intensity

	TFP	**Labour productivity**	**Capital productivity**	**Capital intensity**
Lagged migration intensity	-0.005	-0.027	0.024	-0.051**
	(0.026)	(0.030)	(0.032)	(0.019)
Lagged real GDP growth	0.071	0.018	0.180***	-0.162***
	(0.059)	(0.054)	(0.053)	(0.027)
Lagged investment rate	0.021	0.066	-0.114	0.180***
	(0.113)	(0.104)	(0.145)	(0.054)
Lagged population growth	-0.356**	-0.230	-0.613**	0.383**
	(0.174)	(0.172)	(0.233)	(0.177)
Lagged unemployment rate	0.110**	0.088*	0.163***	-0.075*
	(0.047)	(0.049)	(0.058)	(0.037)
Lagged real compensation growth	0.129***	0.147***	0.025	0.122**
	(0.044)	(0.042)	(0.065)	(0.048)
Tertiary education share	-0.034	-0.035	-0.002	-0.033
	(0.045)	(0.043)	(0.065)	(0.057)
Observations	647	647	647	647
Countries	27	27	27	27
Within R^2	0.069	0.059	0.119	0.178
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are annual log changes multiplied by 100. Migration intensity is lagged one year. Control variables are lagged one year and include real GDP growth, the investment rate, population growth, the unemployment rate and real compensation growth; the tertiary-education share is contemporaneous. Standard errors clustered by country are in parentheses. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A 3: Robustness: Distributed Lag in Migration Intensity

	TFP	**Labour productivity**	**Capital productivity**	**Capital intensity**
Migration intensity	-0.036	-0.020	0.023	-0.043
	(0.027)	(0.040)	(0.026)	(0.035)
Lag-1 migration intensity	-0.012	-0.051*	-0.012	-0.039
	(0.026)	(0.027)	(0.035)	(0.033)
Lag -2 migration intensity	0.053	0.060	0.017	0.043
	(0.037)	(0.041)	(0.038)	(0.039)
Cumulative migration intensity	0.006	-0.011	0.028	-0.039
	(0.030)	(0.035)	(0.038)	(0.039)
Lagged real GDP growth	0.070	0.016	0.172***	-0.156***
	(0.058)	(0.051)	(0.053)	(0.022)
Lagged investment rate	0.052	0.087	-0.086	0.173***
	(0.111)	(0.103)	(0.150)	(0.057)
Lagged population growth	-0.671**	-0.535	-0.712**	0.177
	(0.288)	(0.334)	(0.314)	(0.263)
Lagged unemployment rate	0.116**	0.095**	0.180***	-0.085**
	(0.042)	(0.043)	(0.059)	(0.039)
Lagged real compensation growth	0.146***	0.169***	0.048	0.122**
	(0.051)	(0.042)	(0.079)	(0.053)
Tertiary education share	-0.011	-0.006	0.038	-0.044
	(0.045)	(0.044)	(0.072)	(0.072)
Observations	613	613	613	613
Countries	27	27	27	27
Within R^2	0.084	0.078	0.120	0.180
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are annual log changes multiplied by 100. The specification includes current and two lags of migration intensity; the cumulative coefficient is their sum with a combined standard error. Control variables are lagged one year and include real GDP growth, the investment rate, population growth, the unemployment rate and real compensation growth; the tertiary-education share is contemporaneous. Standard errors clustered by country are in parentheses. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A 4: Robustness: Country-Specific Linear Trends

	TFP	**Labour productivity**	**Capital productivity**	**Capital intensity**
Migration intensity	-0.046	-0.036	0.046	-0.082***
	(0.032)	(0.040)	(0.038)	(0.028)
Lagged real GDP growth	0.052	-0.021	0.160**	-0.182***
	(0.064)	(0.050)	(0.066)	(0.026)
Lagged investment rate	0.046	0.090	-0.146	0.236***
	(0.131)	(0.127)	(0.169)	(0.053)
Lagged population growth	-0.301*	-0.250	-0.439**	0.189
	(0.171)	(0.193)	(0.206)	(0.161)
Lagged unemployment rate	0.082	0.025	0.188**	-0.163***
	(0.062)	(0.067)	(0.071)	(0.057)
Lagged real compensation growth	0.067	0.069	0.003	0.066
	(0.046)	(0.047)	(0.058)	(0.054)
Tertiary education share	-0.106**	-0.098**	-0.100**	0.002
	(0.046)	(0.041)	(0.043)	(0.041)
Observations	668	668	668	668
Countries	27	27	27	27
Within R^2	0.062	0.045	0.130	0.176
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are annual log changes multiplied by 100. The specification adds a country-specific linear time trend. Control variables are lagged one year and include real GDP growth, the investment rate, population growth, the unemployment rate and real compensation growth; the tertiary-education share is contemporaneous.

Standard errors clustered by country are in parentheses. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A 5: Robustness: Population-Weighted Estimates

	TFP	**Labour productivity**	**Capital productivity**	**Capital intensity**
Migration intensity	-0.002	-0.042	0.037	-0.079*
	(0.038)	(0.025)	(0.053)	(0.040)
Lagged real GDP growth	0.082	-0.033	0.200***	-0.233***
	(0.072)	(0.066)	(0.052)	(0.042)
Lagged investment rate	-0.006	0.089	-0.175	0.264***
	(0.101)	(0.081)	(0.133)	(0.066)
Lagged population growth	-0.262	-0.164	-0.466*	0.301
	(0.211)	(0.230)	(0.237)	(0.282)
Lagged unemployment rate	0.044	0.021	0.082*	-0.062
	(0.037)	(0.037)	(0.044)	(0.044)
Lagged real compensation growth	0.121**	0.130*	0.062**	0.068
	(0.051)	(0.072)	(0.029)	(0.087)
Tertiary education share	-0.047*	-0.087**	-0.027	-0.060
	(0.025)	(0.034)	(0.038)	(0.041)
Observations	668	668	668	668
Countries	27	27	27	27
Within R^2	0.062	0.045	0.130	0.176
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are annual log changes multiplied by 100. Observations are weighted by lagged population. Control variables are lagged one year and include real GDP growth, the investment rate, population growth, the unemployment rate and real compensation growth; the tertiary-education share is contemporaneous. Standard errors clustered by country are in parentheses. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A 6: Robustness: Excluding Small Countries

	TFP	**Labour productivity**	**Capital productivity**	**Capital intensity**
Migration intensity	-0.046	-0.079	0.028	-0.107***
	(0.045)	(0.049)	(0.049)	(0.030)
Lagged real GDP growth	0.087	0.015	0.200***	-0.185***
	(0.072)	(0.062)	(0.057)	(0.023)
Lagged investment rate	0.044	0.106	-0.115	0.222***
	(0.117)	(0.098)	(0.158)	(0.064)
Lagged population growth	-0.498**	-0.467*	-0.626*	0.160
	(0.221)	(0.227)	(0.303)	(0.181)
Lagged unemployment rate	0.096**	0.061	0.159***	-0.098**
	(0.041)	(0.039)	(0.055)	(0.039)
Lagged real compensation growth	0.105*	0.108*	0.035	0.073
	(0.057)	(0.060)	(0.067)	(0.068)
Tertiary education share	-0.046	-0.059	0.030	-0.089
	(0.043)	(0.037)	(0.072)	(0.065)
Observations	573	573	573	573
Countries	23	23	23	23
Within R^2	0.084	0.077	0.127	0.219
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are annual log changes multiplied by 100. The sample excludes countries with average lagged population below 2 million. Control variables are lagged one year and include real GDP growth, the investment rate, population growth, the unemployment rate and real compensation growth; the tertiary-education share is contemporaneous. Standard errors clustered by country are in parentheses. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Table A 7: Robustness: Excluding Crisis Years

	TFP	**Labour productivity**	**Capital productivity**	**Capital intensity**
Migration intensity	0.010	-0.008	0.049**	-0.057**
	(0.024)	(0.037)	(0.023)	(0.023)
Lagged real GDP growth	0.201***	0.120*	0.258***	-0.138**
	(0.067)	(0.062)	(0.080)	(0.059)
Lagged investment rate	-0.073	-0.031	-0.232***	0.201***
	(0.057)	(0.082)	(0.081)	(0.038)
Lagged population growth	-0.578***	-0.542***	-0.620***	0.078
	(0.117)	(0.140)	(0.147)	(0.176)
Lagged unemployment rate	0.070	0.050	0.129***	-0.079**
	(0.042)	(0.044)	(0.041)	(0.036)
Lagged real compensation growth	0.093**	0.154***	0.014	0.141***
	(0.043)	(0.046)	(0.061)	(0.049)
Tertiary education share	-0.054	-0.046	-0.028	-0.018
	(0.039)	(0.040)	(0.049)	(0.051)
Observations	485	485	485	485
Countries	27	27	27	27
Within R^2	0.166	0.123	0.238	0.194
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are annual log changes multiplied by 100. The sample excludes periods 2008-2010 (Great Recession), 2015-2016 (Refugee flows of the mid-2010s) and 2020-2021 (COVID-19). Control variables are lagged one year and include real GDP growth, the investment rate, population growth, the unemployment rate and real compensation growth; the tertiary-education share is contemporaneous. Standard errors clustered by country are in parentheses. *, ** and *** denote significance at the 10, 5 and 1 percent levels.

Artificial Intelligence Use Disclaimer

Regarding the use of artificial intelligence (AI) tools, specifically Microsoft Copilot and Anthropic's Claude, both were used in a complementary manner during the preparation of this dissertation. These tools assisted in this work by providing language editing and grammatical review, refining written explanations, and offering content suggestions to improve academic style.

As a result, AI assistance was limited to support tasks, since no AI tool was used to independently generate the entire content of this master's thesis. Thus, all decisions throughout this work regarding research, literature selection, data collection, variable construction, econometric modeling, statistical analysis, interpretation of results, and conclusions were made, reviewed, and validated by me.

In conclusion, I have reviewed all results obtained with the aid of AI and assume full responsibility for the accuracy and academic integrity of my work throughout this thesis.