Louvain School of Management

Optimising Migration as a Strategic Response to Ageing EU Labour Market Challenges: Policy Tools and Implementation Pathways.

Advanced master’s degree thesis in EU Business and Economic Policy (EBEP2MC).

Submitted by: Mballe Mukete Gilbert
Noma: 5649220
Supervisor: Professor Jean-Christophe Defraigne

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UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management
Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve
Boulevard Emile Devreux 6, 6000 Charleroi, Belgique
Chaussée de Binche 151, 7000 Mons, Belgique
www.uclouvain.be/lsm

Abstract :

This dissertation sought to examine the role of migration as a strategic response to labour market challenges linked to the EU's demographic ageing and how to optimise it. It used a mixed-method approach that combines a systematic literature study of EU-based studies and time-series econometric modelling to analyse the perceived dynamic relationship between demographic ageing, migration, and the labour market. Findings show that migration has enormous potential, which, if optimised, can mitigate labour market gaps, especially in rural settings and sectors like healthcare and agriculture that are physically intense and socially complex, thus contributing to the EU's economic sustenance. To support the optimisation process, the thesis proposes three new frameworks :

I. The Ageing Economy Challenge Mix (AEC-MIX) to identify and prioritise major ageing economy challenges;
II. The Migrant-Led Labour Gap Adjustment Framework (ML-GAF) to match migrant profiles with needy sectors and regions; and
III. The Barriers to Migrant Labour Market Access Framework (BAF-MLA) to identify and dismantle structured obstacles to migrants' employment.

The dissertation concludes with a strategic–operational pathway that links diagnosis, policy design, and programme implementation with actionable guidance for the EU and Member States' policymakers. By so doing, this thesis demonstrates that migration policy optimisation is a veritable multi-level governance tool in addressing the socio-economic implications of demographic ageing in the middle and long run.

Dedication :

I dedicate this thesis to the loving memory of Barbara, my beloved sister, whose passing in March 2025 temporarily killed my desire to finish the said thesis. Her untimely demise completely destabilised my world and sapped the energy and motivation required to finish on time.
Barbara was a source of strength, motivation, and encouragement to me throughout her presence. Even five days before her demise, she found time to uplift my motivation, and her last words were filled with grace, optimism and affection, and they will forever remain alive in my heart as a lasting gift.
Barbara, the shadow of your absence made completing this dissertation more challenging than usual, but your spirit and memory have carried me through to the end. This achievement is therefore dedicated to you, with love and deep gratitude. Although your presence is now absent, you remain forever in my heart.

R.I.P., Barbara.
Mballe Mukete Gilbert.

DECLARATION REGARDING AI TOOL USAGE IN MASTER’S THESIS

Declaration

During the preparation of this advanced master’s thesis, I, Mballe Mukete Gilbert, utilised ChatGPT 5 and DeepSeek for the following purpose:

1. To retrieve relevant literature from different sources: e.g., I used them to identify and retrieve the most cited EU-based studies related to migration, demographic ageing and labour market.
2. To summarise the content of retrieved sources, e.g., articles and webpages
3. To visualise my results, e.g., by creating flowcharts, graphs, and tables.
4. To improve my statistical codes, e.g., I used them to translate my Stata codes into R code.
5. I generally used them to check, enhance, and triangulate sources for a better understanding of relevant concepts.

After each usage of the above tools, I diligently ensure that the contents of the said tools are ok. I therefore take full responsibility for the final content presented in this thesis.

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Chapter 1: Introduction

1.1. Context and Justification

Demographic ageing and migration have both emerged amongst the top challenges of the European Union (EU), with overarching socioeconomic undertones. The combination of a current total fertility rate (TFR) of 1.38 and a life expectancy of 81.4 years, compounded by the expected retirement of the EU baby boomers' generation by 2030, makes demographic ageing a major EU challenge, at least over the horizon of 2050 (European Commission, 2024; Eurostat, 2022; Eurostat, 2025). The above profile is an actual showcase of a particularly worrying and demographically unsustainable future EU workforce that warrants the EU bracing itself up to wrestle with ageing economy challenges, including dealing with labour market gaps, fiscal pressure from pension and healthcare systems, productivity slowdown, and a potential political backlash.

Migration is equally redoubtable and has been historically driven by a wide variety of factors, either natural or man-made, within and around the EU. For instance, the 1960s–1970s migration wave resulted from post-colonial bilateral agreements, and the labour shortages that succeeded WWII caused migrants from South Asia and Northern Africa to move to Europe (Castles et al., 2014). The 1980s–1990s wave resulted from the Cold War conflicts, authoritarian regimes, and ethnic cleansing, bringing about the Vietnamese ("boat people") and the Balkan war refugees (Nations Unies, 2000). The 1990s–2000s wave associated with the expansion of the EU in July 2004 brought about the internal movement of Eastern European citizens to Western Europe (Kapur & McHale, 2005), the 2010–2025 wave was linked to the Syrian War, climate disasters, and authoritarian regimes in Venezuela, leading to the migration of Syrians and Ukrainians to the EU (International Organization for Migration, 2021), and recently the 2020–2025 migration wave was associated with the COVID-19 travel restrictions and technology-driven mobility (OECD, 2021), as well as Russia's recent military operation in Ukraine on February 23, 2023.

Consequently, demographic ageing and migration constitute a complex multidimensional phenomenon capable of shaping or being shaped by socioeconomic and political responses, which can translate into a demographic tool, a response to global inequality, a labour market mechanism, or a policy-managed phenomenon that needs continuous evaluation and management. While EU demographic ageing can be framed as an inevitable problem, migration can be framed either as a problem[1] in its own right (European Commission, 2023) or as a solution[2] to the EU's inevitable

[1] RN and AFD respectively in France and Germany have framed migration as a thread to threat to security, culture, and welfare systems.
[2] Migrant contribute more in taxes than they consume in service (OECD, 2021).

demographic ageing condition, depending on the prevailing political, economic, and social context (European Council on Foreign Relations, 2023).

1.2. The Dissertation's Objective and Importance

Regarding the imposing threats akin to demographic ageing, and heightened with the contested role of migration as a plausible response to demographic ageing challenges in the EU, this dissertation's main purpose is not only to examine the extent to which migration can be a sustainable solution to ageing economy challenges but also to determine how to optimise its role as a sustainable policy logic.

23 of the most cited EU-based studies that have examined the nexus between demographic ageing, labour force dynamics, and migration within the context of the EU have generally focused on migration volumes or the fiscal cost of migration, leading to a myopic representation of major migrant groups, a short study period, and variable gaps. These limitations have led to issues like migrant skill-level omission, migrant regional disparities, static projections, and the ignorance of migrant labour market demand, thus limiting the extent to which migrant-specific questions can be effectively identified, contextualised, prioritised, and addressed sustainably. For instance, critical questions related to migrant skill matching and migrant labour demand in rural EU settings. This dissertation seeks to address these gaps by critically examining the extent to which migration can mitigate ageing economy challenges, with emphasis on labour market gaps induced by demographic ageing in the EU through a mixed-method approach. This approach combines a systematic literature study with time series econometric modelling to address some of the major shortcomings that previous studies that have examined the subject might have failed to sufficiently address.

1.3. Link of Purpose with Main Research Question

The main purpose of this study is therefore to examine whether migration has a legitimate potential to address labour market challenges associated with EU demographic ageing. This study sought to answer one fundamental question: "To what extent can migrants mitigate labour market challenges induced by demographic ageing in the EU? To answer this fundamental question, this study hypothesises that "Demographic ageing increases labour market gaps" and that "Migration reduces labour market gaps caused by demographic ageing." To effectively test these hypotheses and answer the main research question, we first identified the major EU labour market gaps that can be associated with demographic ageing. Second, we investigate the perceived dynamic relationship between demographic ageing, migration, and labour market dynamics. By understanding the said dynamics, this study further clarifies the perceived link between them. This study also aims to provide the EU policymakers and their member states with a solution ecosystem composed of three frameworks that will support them in anticipating and addressing the adverse effects of ageism on the EU labour market and its potential impact on the overall sustainability of the EU's ageing economy.

The remaining part of this dissertation is organised as follows: Chapter 2 outlines the literature study process and its major findings. Chapter 3 addresses the quantitative dimension of this study with a detailed description of the quantitative analysis process. Chapter 4 presents, interprets, and comments on major results of the quantitative analysis process. Chapter 5 discusses findings from both the literature study and quantitative analysis, and, most importantly, it introduces an ecosystem of frameworks developed within the context of this dissertation as a contribution to optimising migrant labour within the EU labour market. Chapter 6 concludes by summarising the answers to the main research question.

Chapter 2: Overview of Literature Study

2.1. The literature study process.

In the course of this study, 23 highly influential studies on the role of migration in responding to labour market challenges induced by demographic ageing in the context of the EU were systematically examined. The selection was randomly done with AI support based on three key terms: 'Demographic Ageing’, 'Labour Market Gaps’, and ‘Migration’ in EU-based studies published from 2015 onwards. The goal of the literature study was first to understand the current state of knowledge on EU-based migration studies and to identify major gaps in the literature while gathering relevant facts to address the central research purpose. Once again, the central research purpose was to determine whether migration has legitimate potential to address labour market gaps induced by demographic ageing in the EU and how migration could become a sustainable response to ageing economy challenges. This goal is achieved by critically examining influential studies to identify relevant emerging themes, debates, methodological approaches, and gaps to justify the selection of a suitable model for this dissertation.

2.2. Thematic Discussion of Findings from the Literature Study

2.2.1. Major Ageing Economy Challenges in the EU

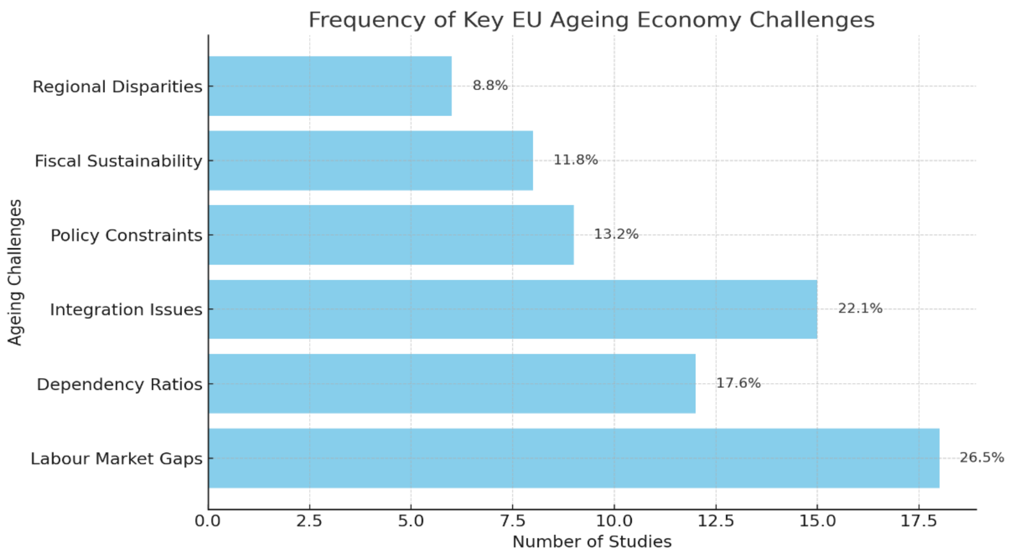


Figure 2.2.1 outlines the major challenges of the ageing EU economy as highlighted across the consulted EU-based studies. Based on the figure, six major challenges characterise the ageing EU economy, with labour market gaps, integration issues, and dependency ratio featuring as the most

outstanding ones, followed by policy constraints, fiscal sustainability, and regional disparities. These findings have led us to conclude that the most outstanding ageing economy challenges within the context of the EU, over the period covered by the studies, are labour market challenges, which constitute the main focus of this dissertation.

2.2.2. Impact of Demographic Ageing on EU Labour Market Dynamics

The literature study sufficiently explains how demographic ageing is a redoubtable threat to the economic sustainability of the EU due to its multiple negative effects on the labour market dynamics and, by implication, its economic growth. For instance, Ghio et al. (2022) and Marois et al. (2020), through their respective studies, have demonstrated that as a population ages, the workforce necessarily shrinks, which impacts the demand and supply of labour, productivity, wages, and human capital. In the same vein, (De Beer, 2024; Pinkus & Ruer, 2025) have emphasised that an ageing population necessarily leads to an ever-increasing old-age dependency ratio, which is found to have a reducing effect on pension, healthcare, and welfare systems across the EU. Furthermore, Chand (2024) and Strupczewski (2024) have warned about the imminent doubling of the EU's dependency ratio on the 2050 horizon, and Chand even estimated a 15% drop in the Central and Eastern European (CEE) population in the same time frame.

The above findings clearly show that labour supply in the EU is not only expected to drop to different extents across different regions but also expected to drop in different sectors of the EU society, especially in the sectors of agriculture, construction, healthcare, and social welfare systems. These startling findings indicate prospects of a slowing EU economic growth with the possibility of escalating into a more violent fiscal pressure amidst a growing EU-dependent population if nothing is done to pre-empt it (Chand, 2024; European Commission, Joint Research Centre et al., 2019; Pinkus & Ruer, 2025; Scott & Tegunimataka, 2020). In a nutshell, findings underscore the inhibiting role of demographic ageing on the EU's economic sustainability, with an increased risk of widening economic disparity amongst major EU regions due to the accumulated disproportional regional effects in the long term. How, then, can the inhibiting impact of demographic ageing be arrested?

2.2.3. Role of Migration in EU Labour Market Adjustment

Numerous studies have shown that migration plays a significant role in addressing ageing labour market gaps, as it helps counterbalance the negative effects of demographic ageing, boosts and sustains the supply of labour, and replenishes regional and sectoral gaps (Spielvogel & Meghnagi, 2018). As expounded by Marois et al. (2020), migration enhances overall labour force productivity in the EU through two mechanisms: firstly, it generally expands the EU labour force participation rate to the extent to which migrants step into the EU labour market. Secondly, it contributes to the improvement of overall educational attainment in the EU. Put together, both mechanisms are found to generally offset the dependency burden in the EU economy. Nevertheless, De Beer (2024) emphasises that only migrants whose marginal productivity in the labour market exceeds the EU average GDP per capita can positively contribute to the EU's national welfare. Furthermore, numerous studies have demonstrated that the benefit of migration is contingent on quality integration, effective regional policies, and migrant-specific age, fertility, and skill set (European Commission, Joint Research Centre et al., 2019; Pinkus & Ruer, 2025; Scott & Tegunimataka, 2020).

However, although migration has a mitigating effect on ageing labour market challenges, its role is nuanced by the fact that its effectiveness is disproportionate across the different EU spatial allocations, like the regional and rural vs. urban divide (Ghio et al., 2022). These studies collectively highlight the fact that while migration is an important component in responding to ageing labour market challenges, its intervention is only a major component of the solution set; optimising the role of migration and complementing it with other factors will go a long way to slow the effect of EU demographic ageing. How then can the role of migration be optimised?

2.2.4. Barriers to Migrant Employment

The major barriers to migrant employment in the EU labour market are wide and diverse and include legal, administrative, linguistic, and educational attainment; skill set misalignment; lack of coordination between policy actors; and discriminatory challenges in general (Fasani, 2024; Galgóczi & European Trade Union Institute, 2021). In this regard, Van Leeuwe (2006) has noted that migrants in higher age brackets are confronted with structural barriers to accessing employment in the EU due to the perceived wage-productivity misalignment at old age. In addition, there are political constraints, which most of the time translate into political reluctance for migrant-centric legislation to achieve common consensus in EU decision-making cycles ((Strupczewski, 2024). And finally, Chand (2024) also highlighted that cultural barriers among Central and Eastern European (CEE) countries expose them to social resistance to immigration from non-EU countries, thus limiting them to an external labour market solution. The above examples collectively highlight the perceived immobility and the relatively high cost of productivity attributed to older migrant workers, which kind of dilutes the hiring incentive of recruiters in the EU in general. How can the barrier to migrant employment be effectively busted?

2.2.5. Results of Literature Gap Analysis: Quantifying qualitative insights

Table 2.3.1.1: Overview of Data Gaps Based on 20 Selected Studies

(Total Gaps = 100% | Total Studies = 20)

Gap Category	Subcategory	Studies Affected (n/20)	% of Total Gaps	Priority
Representation: 45%	Skill-level omission	70% (**14/20)**	31.5%	🔴 **High**
	Regional disparity	75% (**15/20)**	33.75%	🔴 **High**
	Urban bias	60% (**12/20)**	27%	🟠 **Medium**
Time Range: 30%	Pre-2020 data	80% (**16/20)**	24%	🔴 **High**
	Static projections	40% (**8/20)**	12%	🟢 **Low**
Methodological: 25%	Labour demand ignored	60% (**12/20)**	15%	🟠 **Medium**
	Legal status omitted	50% (**10/20)**	12.5%	🟢 **Low**
	Integration policies unlinked	50% (**10/20)**	12.5%	🟢 **Low**

2.2.5a. Literature Representation Gap: 45 percent

Table 2.3.1.1 summarises the results of the data gaps analysis based on 20 selected studies, and the results highlight three major gap categories: representation (45%), time frame (30%), and methodological variables gaps (25%). This implies that 45% of the gaps in the consulted literature are due to incomplete representation of major migrant groups or units. For instance, 75 %t of the studies have regional disparities, prioritising the Western/Northern regions over Eastern/Southern regions, as in ((Pinkus & Ruer, 2025; Valsta, 2017). About 70 percent of the studies are biased in terms of skill level; they tend to focus more on low-skilled migrants at the expense of high-skilled migrants (Marois et al., 2020; Spielvogel & Meghnagi, 2018), and 60 percent of the studies have overfocused on migrants in urban settings rather than those in rural areas (e.g., Chand, 2024; Ghio et al., 2022). This incomplete representation of studies affects the quality of policy orientation, which in turn negatively affects policy effectiveness. For instance, if a study fails to capture the reality of migrants in a rural setting, its resulting policy recommendation may fail to respond to rural-specific labour shortages. Likewise, if 70 percent of policy research ignores high-skilled migrants, it might be difficult to know which migrant skills to attract in a specific region or rural/urban setting. The above findings imply the need for studies with more representation, including migrants in rural spatial allocations, more regional representation, highly skilled migrant, the demand and supply of migrant labour, etc. How then can the representation equation be successfully addressed?

2.2.5b. Literature Time Range Gap: 30 percent

The literature gap analysis also reveals that the time range gap represents 30 % of the total gaps. This implies that 30% of the studies have used data that is either static or out of scope. For instance, 80 % of the studies (e.g., (Billari, 2022; Charles-Edwards et al., 2025) have used pre-2020 data, which most probably cannot reflect labour market shocks attributable to the COVID-19 pandemic, as well as the impact of refugees associated with Russia’s military operations in Ukraine. In the same vein, 40% of the studies have static projections, implying a lack of dynamic migrant turnover (e.g., (Amran et al., 2019; Grenčíková et al., 2023). This is the case when a migrant worker leaves their host country after five years. These gaps are important to consider because, for instance, the Ukraine war brought in many refugees, most of whom filled ageing sector jobs. This means that the dynamism of demographic ageing and migrant trends may not be reflected in static models, which might cause the migrant retention rate to be underestimated, thus undermining policy focus. The above-stated cases generally call for the need for model designs that can accommodate dynamic parameters, which are found to be common in migration and labour market dynamics, especially in the context of ageism.

2.2.5c. Methodological Variable Gap: 25 percent

The systematic analysis of data gaps also hints at the methodological variable weakness in about 25% of the studies consulted. This figure implies that a quarter of the studies consulted have issues with the study design. The findings show that 60 % of the studies failed to capture sector-specific labour demand (Aldieri et al., 2024; Van leeuwe, P., 2006), while 50 percent failed to include undocumented migrants as in (Fasani, 2024; Galgóczi & European Trade Union Institute, 2021), and finally, half of the studies failed to establish the important link between integration policies and migrant labour outcome as in (De Coninck & Solano, 2023). The analysis equally failed to find any study design that has combined high-skilled migrants in a rural ageing context with dynamic turnover.

2.2.6. Identified Gaps in Methodological Approaches

Besides the data gaps outlined in the previous section, the literature study also reveals that the nexus between EU demographic ageing, labour market shortage, and migration has been extensively examined using a wide panoply of methodological approaches, including methodological shortfalls (in terms of decomposed analysis, intervention measurement, and causality) and modelling approach (in terms of the models' inherent assumptions), as well as policy relevance.

Table 2.3.1.2: Methodological Approaches in Reviewed Studies

SN	Methodological Category	% of Studies	Key Techniques
1	**Quantitative Modelling & Simulation**	32%	- Microsimulations - Demographic projections - Scenario analysis
2	**Mixed-Methods Approaches**	20%	- Surveys - Case studies - Interviews - Secondary data synthesis
3	**Policy & Case Study Analysis**	16%	- Policy reviews - Institutional analysis - Comparative case studies
4	**Comparative Stats & Reviews**	16%	- Cross-country benchmarking - Systematic reviews - Meta-analysis
5	**Econometric Causal Analysis**	12%	- Instrumental variables (IV) - RCTs - Fixed-effects
6	**Descriptive Micro-Data Analysis**	4%	- National administrative data - Descriptive statistics

Table 2.3.1.2: Summarises findings from methodological approaches used in reviewed studies

2.3.1.2a. Quantitative Modelling & Simulation

According to Table 2.3.1.2, the majority of the studies reviewed (32%) have used quantitative modelling and simulation methodology, comprising microsimulations, demographic projections, and scenario analysis techniques. For illustration, Marois et al. (2020) have used microsimulation and scenario analysis to investigate population ageing, migration, and productivity in Europe. While

Amran et al. (2019), in their quest to understand how different demographic scenarios can alter or be altered by demographic ageing and labour market dynamics within the context of the EU, adopted both macro- and micro-simulation approaches. Spielvogel and Meghnagi (2018), whose interest was rather on discovering the extent to which migration can influence the expansion of the EU labour force participation in the horizon of 2030, preferred to use the cohort-component projections techniques. Each investigation technique is prone to different research objectives. Notwithstanding, modelling and simulation approaches are generally strong in providing high granularity, futuristic projections, and policy-relevant scenarios. As a result, they appear to be prone to assumptive scenarios and static assumptions that may lack relevant empirical validation.

Given the case of Marois et al. (2020), who in their study hypothesised that the dependency ratio of the EU will follow the Canadian immigration pattern, implicitly assuming that other accompanying measures and policy environments, such as perfect integration of migrants, will necessarily succeed. If in the real-life scenario, such is not the case, it will simply nullify the applicability of the said projection. In another case, Amran et al. (2019), in one of their scenarios, loosely assumed that the labour productivity of migrant education is fixed. This assumption is no longer realistic in the current dispensation, spatially in the era of big data, robotisation, and AI, where automation is simply disrupting the traditional connection between education and migrant labour productivity.

2.3.1.2b. Mixed-Methods Approaches

Mixed-methods approaches equally hold an important representation and account for about 28% of the studies reviewed. It generally includes some combination of quantitative and qualitative techniques. For instance, Fóti and the European Foundation for the Improvement of Living and Working Conditions (2024) have used the Survey on FRA and IOM, administrative data from national agencies, case studies, and country-level comparisons to study the social impact of migration with emphasis on the challenges associated with Ukrainian refugee integration in the EU. To demarcate the effects of natural ageing from those of migration. Ghio et al. (2022) have used demographic decomposition techniques with spatial cluster analysis techniques to highlight major patterns across rural, urban, and intermediate areas. Mixed methods generally have the advantage, given that they help to associate real-time quantitative data with qualitative insights to facilitate the contextual understanding of demographic and labour market dynamics in different contexts. However, they usually require data fragmentation, which can limit long-term tracking of parameters and thus fail to quantify qualitative impact. In this context, combining refugee data from UNHCR with national administrative data could have rendered cross-country comparison less robust.

2.3.1.2c. Policy and Case Study Analysis

Policy and case study analysis methodological approaches have had a fair application (16%) and translate into policy reviews, institutional analysis, and comparative case studies. For instance, the Council of Fóti & Conditions (2024) and the European Foundation for the Improvement of Living and Working Conditions (2024) combined policy analysis with case study review of EU data, case study consultation with civil society organisations and migrant integration programmes, and comparative country analysis to answer questions related to EU demographic ageing. Pinkus and Ruer (2025), on their part, used a policy-oriented analytical study to examine ageing inequalities across the EU. Their methodological technique generally has the merit of enabling the comparison of local versus regional focus. By so doing, the said approach helps, on the one hand, to identify practical policy insights. On the other hand, it provides no econometric insights and cannot quantify qualitative impacts, which exposes it to political risk bias. For instance, the Fóti & European Foundation for the Improvement of Living and Working Conditions (2024) study endorses migration as a potential solution to demographic ageing without any causal analysis to showcase its economic profit. In the same manner, Pinku & Ruer (2025) have helped to provide a regional comparison but failed to quantify how migration can mitigate EU labour market shortages, which is equally relevant for effective policymaking.

2.3.1.2d. Comparative Stats & Reviews

Comparative statistics and review methods also account for 16% of studies consulted and are generally implemented through cross-country benchmarking, systematic literature reviews, and meta-analysis. For example, Scott & Tegunimataka (2020) used a narrative review approach to synthesise demographic- and economic-related studies, while Valsta (2017) used quantitative demographic and labour analysis with the Jobs Group Demography Tool to synthesise EU-based studies that have applied macroeconomic analysis, demographic projections, and policy evaluations. Both techniques have generally helped to assess cross-country trends and to see evidence. Nevertheless, both approaches suffer from a lack of primary data and weak causal inference, which may limit the generalisability of their results. The fact that Valsta (2017) relied solely on secondary data may have deprived its results of the grassroots realities, such as the experience of the informal labour market or the socioeconomic reality of the host community. Similarly, Scott and Tegunimataka (2020) in their study attributed the weakening of the ageing effect in the labour market to migration without controlling for the effect of other variables such as rising native fertility.

2.3.1.2e. Econometric Causal Analysis

The econometric causal analysis methodological approach can be said to have been applied in 12% of the studies reviewed. The studies have specifically employed the use of instrumental variables (IV), RCTs, and fixed-effects models to investigate the nexus between the EU's ageing labour force and migration. Specifically, Aldieri et al. (2024) have used panel regression with OLS and 2SLS to estimate the impact of immigrant presence on native employment in three age groups, notably the 15–24, 25–34, and 35–55 age groups. Guzi et al. (2023) draw from the Blinder–Oaxaca decomposition approach to decompose the EU labour market gaps into their constituent explained and unexplained components. The study also examined the association of policy changes with EU labour market gaps across time and countries. Both approaches offered robust causal inference; however, their results are most likely to be affected by data limitation issues related to missing or a lack of data on certain newly incorporated EU member states. This limitation may have caused heterogeneity in migrant groups that are not considered in the model. For instance, in (Aldieri et al., 2024), Germany and the Netherlands were not considered due to a lack of data linked to missing census data, even though those countries represent major refugee populations.

2.3.1.2f. Descriptive Micro-Data Analysis

Descriptive microdata analysis is the least used methodological category and accounts for only 4% of the studies, and includes national administrative data and descriptive statistics (Van Leeuw, 2006). Van Leeuwe used descriptive analytics, i.e., micro-level statistical analysis, to show that demographic ageing is a critical challenge to labour supply. This method has helped to provide employment insights by decomposing the workforce into demographic characteristics (age, gender, income, and employment history); however, it is country-specific and narrow in scope and may fail to provide the link between migration and the labour market across the EU.

2.3. Synthesis of Literature Findings, Research Gap Profiling, Method Justification

The literature study has led to the conclusion that although the relationship between demographic ageing and labour market performance is dynamic, demographic ageing has a reducing role, which in turn inhibits the EU's long-term economic sustainability. Migration is a significant component in adjusting age-linked labour market gaps in association with quality integration programmes, effective regional policies, automation, and migrant-specific age, fertility, and skill sets. Migrants' labour market access and integration are generally hampered by legal/administrative hurdles, mismatch of labour/human capital, coordination/institutional failures, discrimination/socio-cultural bias, and spatial and sectoral mismatch.

45% of the studies have a biased or misrepresented view of relevant migrant groups and appear to focus more on low-skilled migrants in urban areas in Western/Northern regions of the EU. 30% of the studies have gaps related to the data coverage period; 80% of them used a pre-2020 data range, and 40% used static modelling. 25% of the studies have methodological variable bias, which includes ignorance of migrant labour market demand (60%), the omission of migrants' legal status (50%), and policy integration (50%). Only 12% of the studies have used econometric causal analysis methodical approaches that include using IV, RCTs, and fixed-effects techniques to examine the nexus between demographic ageing, labour market gaps, and migration.

Based on the above conclusions, this study resolved to use the VAR framework to address some of the major shortcomings identified in previous studies that have used econometric causal analysis methodology. As can be inferred from Table 2.3.1.2, studies that have adopted econometric causal analysis methodical approaches have focused on static models or cross-section panel analysis, but none have specifically used time-series econometric techniques (VEC, ARDL, Granger causality), which the current study has adopted. The VAR framework enables the estimation of both long-run and short-term labour market dynamics, cointegration, adjustment speed, and reverse causality.

This study strives to mitigate the identified data gaps by including the longest data range possible to consider post-COVID and the Ukrainian refugee influx. It equally attempts to fill the identified gaps by developing an ecosystem of three frameworks (AEC-Mix, ML-GAF, and BAF-MLA) presented in chapters 5 and 6. We argue that adopting the three frameworks as an EU-wide labour market strategy will help to optimise the full potential of migration and mitigate the effect of demographic ageing in the EU economy.

Chapter 3: Methodology

3.1. Research Approach: Methodological framework.

Owing to the perceived complex nature of the link between migration, labour market dynamics, and demographic ageing, this study adopted a twofold approach, consisting of a systematic literature study complemented by a quantitative, empirical research approach. In keeping with the principal goal of this dissertation, we capitalised on available secondary data retrieved from the database of the World Bank's World Development Indicators (WDI) on October 28, 2024, and May 2025. Relevant time series econometric techniques, the R software package, and LLM have been widely used to examine the trend of relevant indicators, test hypotheses, and estimate the direction of causality amongst proxy indicators. In some cases, the flexibility of LLM was used to quickly search, visualise, and triangulate sources and to generate schematic diagrams.

The rationale behind this approach includes free access to a wide variety of relevant variables on EU demographic ageing, migration, and labour markets in the 27 EU member states, spanning the period 1960–2023. This approach also leveraged the free access to R software and LLM to ensures the use of quality secondary data sources and analytical robustness, which is preceded by a workflow comprised of three main steps: data retrieval and compilation from relevant sources; data preparation and cleaning; and exploratory data analysis (EDA) to inform variable selection and time series modelling technique.

3.2. Description of Quantitative Analysis Process

3.2.1. Step 1: Data Collection & Compilation

Data collection and compilation consisted of using the relevant R-packages, the API of the WDI database, the Eurostat database, and literature to extract and compile a shortlist of 21 relevant variables conveniently organised into five indicator categories as shown in Appendix_1. The R scripts for the quantitative analyses process are available upon request.

Table 3.2.1: List of most relevant variables considered in the analysis (see Appendix _1)

3.2.2. Step 2: Data Preparation & Cleaning

The data preparation and cleaning process included renaming the shortlisted variables for easy identification, dealing with missing values, and generating new variables in preparation for preliminary analysis to comply with time series modelling requirements. R's "DataExplorer" package was used to profile the data for inspection and necessary actions.

According to the data profile report, the dataset compiled for this study is composed of 21 variables related to EU demographic ageing, migration, labour market gaps, economic context, and relevant sectors, with 64 possible annual EU aggregates ranging from 1960 to 2023. 30% (8) of the variables were found to have zero missing values, 9.5% (2) have less than 35% missing values, 47% (10) have between 46% and 79% missing values, and 4.7% (1) have over 81% missing values. Based on this report, 8 of the variables are rated good, 2 are considered acceptable, 10 are considered undesirable, and 1 variable was excluded. The overwhelming majority of the variables are skewed (positively or negatively), with very few approximating a normal distribution. The skewness was addressed through a log transformation and differencing to stabilise the distribution before modelling. A very few number of variables have zero or near-zero variance, implying a constant or near-constant variation across observations, and were excluded from further processing. The missing values of "TFR", "total_health_exp", "migrant_stock", and "health_exp_per_elderly" for 2023 were replaced with those obtained from Eurostat[3] and manually imputed into the dataset using relevant R-code values (Eurostat, 2025).

3.2.3. Step 3: Exploratory Data Analysis (EDA)

This step consisted of calculating the descriptive statistics of all shortlisted variables to summarise their respective distributions, central tendency, and variations. A subset of the dataset was used to conduct Pearson correlation analysis to capture the strength and direction of linear relationships amongst variables within and between indicator categories to identify obvious cases of multicollinearity and the final selection of proxy indicators per category. The same subset was used to conduct a principal component analysis (PCA) to reduce dimensionality and detect the latent structure needed to further inform the variable selection process for modelling. Finally, the time series of proxy indicators were visualised to identify relevant deterministic properties, and unit root analysis was conducted to evaluate their temporality and stationarity necessary for final model selection and specifications.

[3] Eurostat. (2025, March 7). Record drop in children being born in the EU in 2023. European Commission. Retrieved June 20, 2025, from https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20250307-1

3.2.4. Correlation Analysis Process and Results Summarised

Table 3.2.2: Correlation matrix table (see Appendix_3).

As can be inferred from the resulting correlation matrix, amongst indicators of demographic ageing, there exists a strong positive (|r| > 0.8) correlation among TPA_65_plus, OADR, and LifExp and a weak negative correlation among TPA_65_plus, TFR, and OADR. This implies that TPA_65_plus, OADR, and LifExp capture similar demographic patterns, suggesting that ideally only one of the pairs should be included in the final model to prevent collinearity. The moderately negative correlation among TPA_65_plus, TFR, and OADR suggests that fertility rate drops as population ages, which is consistent with theoretical expectations. There exists a strong positive correlation among indicators of migration. The correlation between NMgr and remittances, MgrStock, with MgrStock_pct falls between 0.72 and 0.75, suggesting that NMgr could serve as a positive proxy indicator for migration, and the other variables could be dropped from the final model to reduce multicollinearity. There is a strong positive correlation amongst LFPR, emp_serv, and serv_share (|r| > 0.87), suggesting that any of the three variables could be maintained in the final model.

3.2.5. Result of Principal Component Analysis (PCA) Explained.

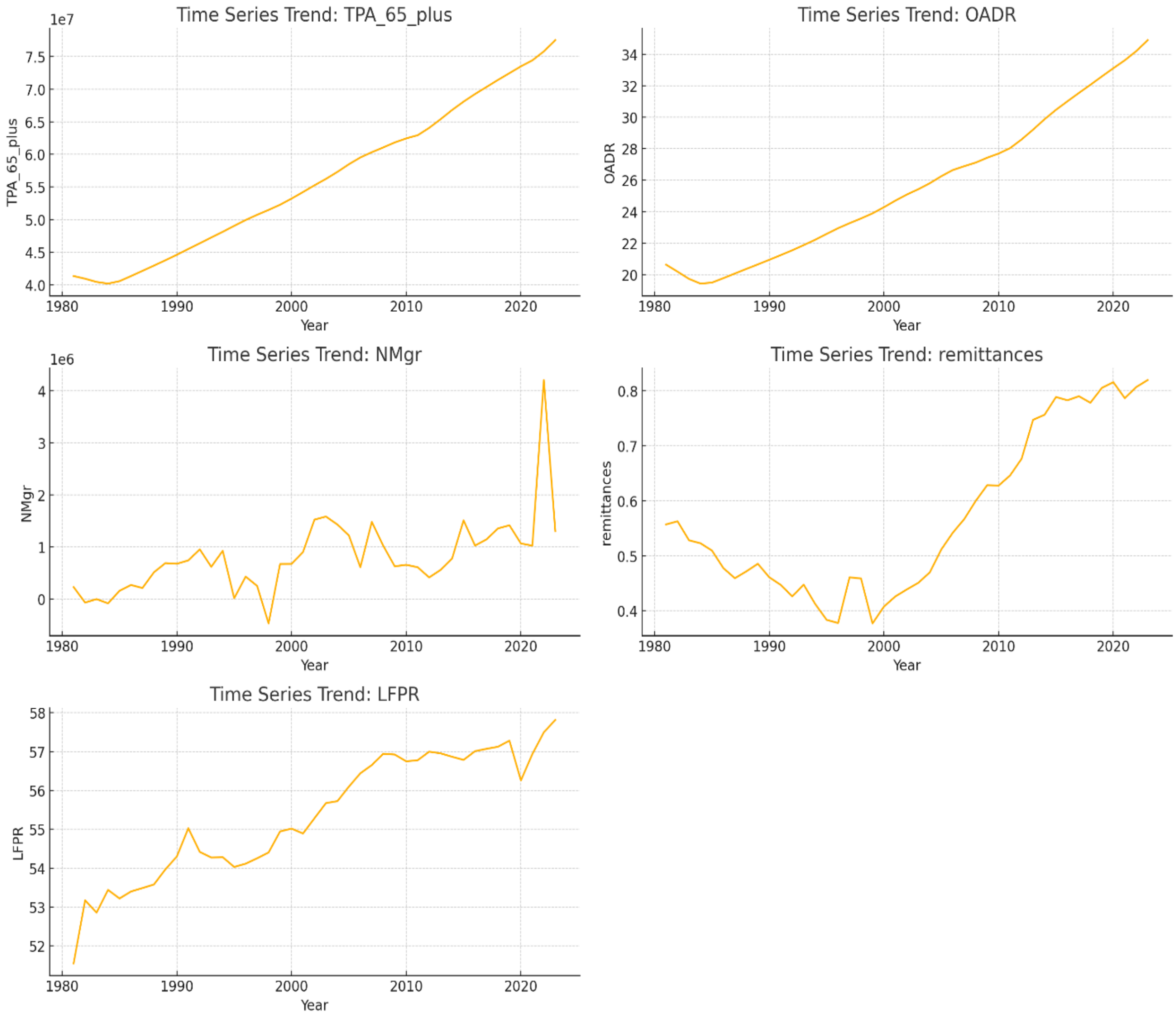
Table 3.2.3: Explained Variance by Component (see Appendix_2)

The results of the principal component analysis reveal that the first two principal components (PC1 and PC2) explain over 87 percent of the explained variance in the dataset, which means that the majority of the variability in the dataset is conveniently captured in PC1 and PC2, with a relatively small amount of information lost. The PC1 is weakly negatively loaded on demographic ageing variables (TPA_65_plus, OADR, LifExp), migration (MgrStock, NMgr, remittances, and RefuPop), and labour market indicators (LFPR), suggesting that it captures ageing, migration, and labour market dynamics. PC2 is driven by TFR, EmpR, RefuPop, health_exp, and exp_elderly. This reflects the dynamics of fertility, employment, migration, and fiscal pressure. Variables with high mutual loading from the same variable category were considered redundant and dropped from the final model where necessary. "Based on PCA, we had the option of selecting one variable amongst TPA_65_plus, OADR, and LifExp (ageing) and among NMgr., remittances, RefuPop (migration), and LFPR (labour market) as non-redundant indicators to be included in the final model. This was based on the fact that variables that have equal contribution in the same PC are highly correlated, while those in different PCs are uncorrelated, as a way of addressing multicollinearity. Concerning findings from correlation and PCA analysis, taking cognisance of the desire to align the current analysis with the main research question, coupled with the desire for easy interpretation and policy relevance, this study settled on two models: one for hypothesis testing and the other one focused on investigating the nature of the perceived complex relation amongst proxy variables retained. We retained the labour force participation rate to proxy for the labour market gap; net migration, age dependency ratio, and the percentage of the population above 64 years of age as the major predictors of labour market gaps; and GDP growth and total fertility rate as the major control variables.

3.2.6. Unit Root Analysis Process and Results Summarised

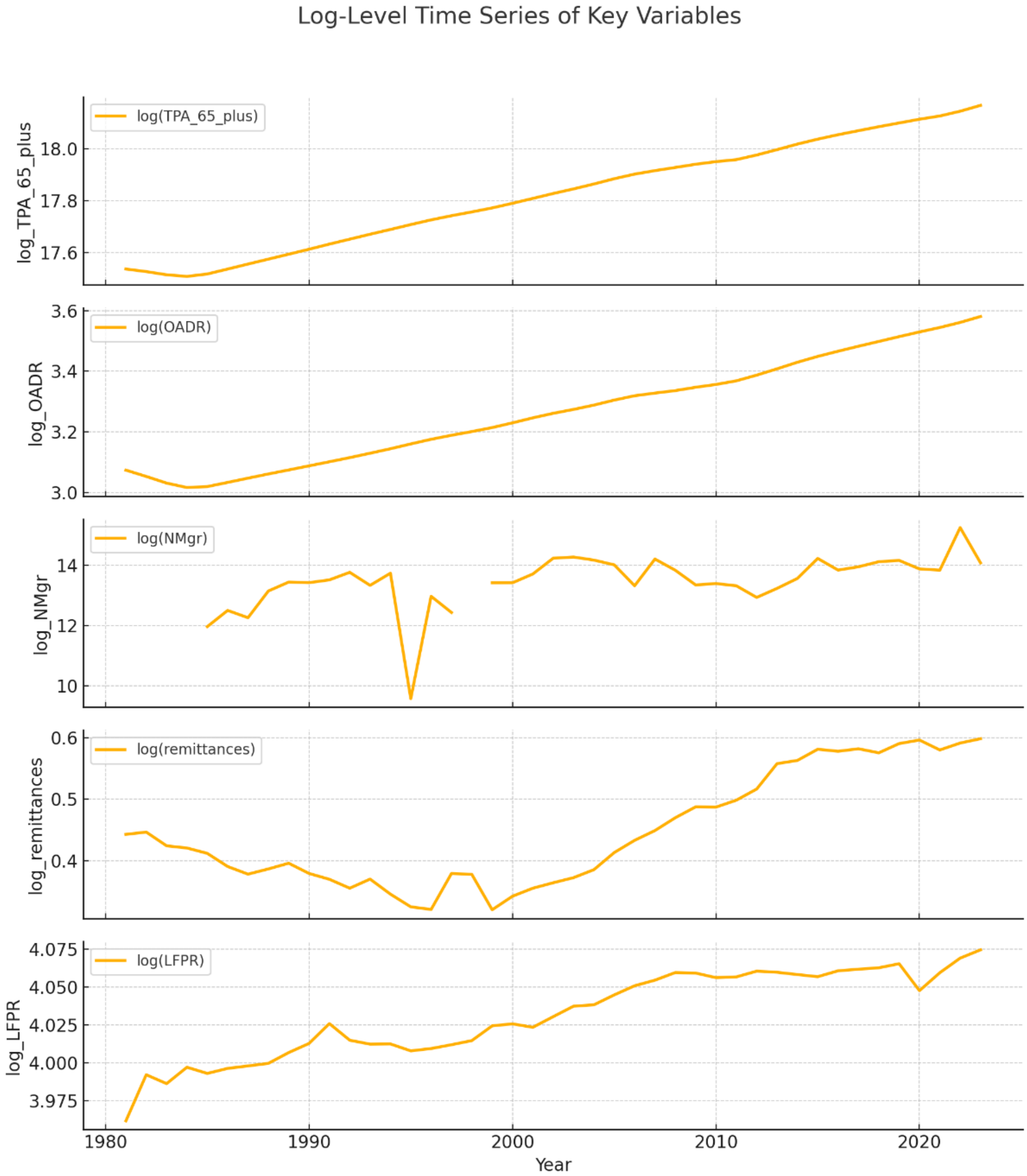
The results of correlation and PCA further informed the final selection of variables to include in the model. However, to ensure that the right time series model is selected and properly calibrated, relevant R-packages were once again used to first do a qualitative evaluation of each time series before conducting a formal unit root test for validation. The qualitative evaluation consisted of visually inspecting the time series plot of each variable at the level, log-level, and differenced log-level to identify the main deterministic property of each series and also to determine the optimal lag length to enable proper specification in the formal unit root test and modelling. Findings from visualisation and the determination of optimal lag length led to the implementation of the Augmented Dickey-Fuller (ADF) tests, and the KPSS test was used as a confirmatory test. Figure 3.2.1 below visually summarises the properties of shortlisted proxy indicators.

Figure 3.2.1: Summary results of graphical analysis of variables at the level



The above figure is a visual representation of the time series of shortlisted variables at the level. Overall, the figure indicates that the most visible deterministic characteristic is the existence of a more or less stable trend with no visible intercept.

Figure 3.2.2: Summary results of graphical analysis of variables at the Log-level.



The above figure is a visual representation of the time series of shortlisted variables at the log level. Overall, the graphs show that the most visible deterministic characteristic is the existence of a more or less stable increasing trend with no intercept.

Figure 3.2.3: Summary results of graphical analysis of variables at differenced log-level

The above figure is a visual representation of the time series of all shortlisted variables at the differenced log-level. The most significant deterministic characteristic is the existence of a mean that appears to be constant (i.e., the mean oscillation is more or less close to zero). The effect appears to be induced by the effect of first differencing.

Table 3.2.4: Summary of variables' deterministic properties (level, log-level, differenced log-level) see Appendix_4

Tables 4.2-4.4 summarise the results of the lag length selection and formal unit root testing process for the shortlisted variables. We used the ADF test and confirmed the results with the KPSS test. In the ADF test, the null hypothesis assumes that each time series has a unit root (i.e., is non-stationary), which implies that when the P-value < 0.05, the null hypothesis cannot be rejected. In the case of the KPSS, the null hypothesis assumes stationarity, which implies that when the KPSS statistic is below the critical value, it confirms the existence of stationarity. Based on the results from both tests, it was concluded that all the variables are non-stationary at the level but become stationary after differencing them at the log-level, which is consistent with the results of visualisation. This conclusion motivates the use of time series modelling, notably the ARDL and VECM.

Model Specification

Based on the results of the preliminary analysis of the various time series, the Autoregressive Distributed Lag Model Specification (ARDL) and its Error Correction Representation were selected. The above specifications are considered suitable for investigating the extent to which migration can mitigate labour market gaps associated with demographic ageing within the context of the EU by testing the relevant hypothesis. The first hypothesis (H1) assumes that demographic ageing increases labour market gaps, and the second hypothesis (H2) assumes that migration reduces labour market gaps caused by EU demographic ageing.

The ARDL model uses log_LFPR (labour force participation rate) as the dependent variable, while log_TPA_65_plus, log_OADR (old-age dependency ratio), log_NMgr (net migration), and log_remittances are used as explanatory variables, and the differenced log-level versions of the same variables were also included in the model. The ARDL was estimated manually using R's dynlm function and the Wald test to check for the existence of cointegration. Based on the positive outcome of the Wald test, the ECM for the short run and error correction terms were equally estimated (i.e., the short-run dynamics and speed of adjustment towards long-run equilibrium). And finally, the residue of the ECM was tested for normality, serial correlation, and heteroskedasticity. The ARDL's outcome is summarised and interpreted in Chapter 4.

Similarly, to investigate the perceived dynamic relationship among demographic ageing, migration, and the labour market, we equally implemented a VECM using relevant R packages. This investigation began by first using the VARselect function to determine the optimal lag length, which was found to be five. Based on the results of the preliminary analysis, the dominant deterministic characteristic retained is the "trend", and both parameters were factored into the Johansen Cointegration Test. The output of the Johansen Cointegration Test and VECM has been summarised in Chapter 4, and the associated R script is available upon request.

3.2.5a. The General Form of the Autoregressive Distributed Lag (ARDL) Model Specification

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=0}^{q} \beta_j X_{1,t-j} + \sum_{k=0}^{q} \gamma_k X_{2,t-k} + \sum_{l=0}^{q} \delta_l X_{3,t-l} + \sum_{m=0}^{q} \theta_m X_{4,t-m} + \varepsilon_t$$

Where:

- y_t is the dependent variable (LFPR).
- x_{it} represents the independent regressors (e.g., TPA_65_plus, OADR, NMgr, remittances),
- p and q_i denote optimal lag lengths.
- α_0 is the intercept term.
- φ_i and β_{ij} are short-run coefficients.
- ε_t is the white noise error term.

This specification enables us to model how current and lagged values of both the dependent and independent variables affect the outcome variable.

3.2.5b. **Error Correction Representation (EC) of the ARDL model**

Error Correction Representation of the ARDL model is expressed as:

$$\Delta Y_t = \phi_0 + \sum_{i=1}^{p-1} \phi_i \Delta Y_{t-i} + \sum_{j=0}^{q-1} \theta_j \Delta X_{1,t-j} + \cdots + \lambda(Y_{t-1} - \delta_0 - \delta_1 X_{1,t-1} - \cdots) + \varepsilon_t$$

The EC representation is conditional on the existence of a long-run equilibrium relationship among the variables; the ARDL model translates into an Error Correction Model (ECM) to capture both short-run and long-term dynamics.

Where:
- Δ represents the first-difference operator.
- $EC_{t-1} = y_{t-1} - \rho_0 - \rho_1 x_{1,t-1} - ... - \rho_k x_{k,t-1}$ is the error correction term derived from the long-run equilibrium relationship.
- λ is the speed of adjustment coefficient, which should be negative and statistically significant if long-run causality exists.

This representation implies that deviations from long-run equilibrium in one period are partially corrected in the next, at a rate determined by λ.

Chapter 4: Presentation of Major Results with Interpretation

4.1. Results of Univariate Analysis

4.1.1. Descriptive Statistics of Major Indicators:

Table 4.1.1. Descriptive Statistics of Major Indicators Considered

	Variable	Mean	Median	SD	Min	Max	Skewness	Kurtosis
1	LFPR (15+)	57.5	57.8	6.70	32.5	84.5	0.187	4.83
2	Emp to Pop (15+)	52.6	52.5	6.22	27.5	73.1	-0.0262	3.11
3	Net Migration	39910.	4416.	170435.	-910475	3366387	7.65	106.
4	Age Dependency Ratio	52.2	51.5	5.70	38.7	76.7	0.842	4.74
5	% Aged 64+	14.0	13.5	3.70	5.77	24.5	0.376	2.46
6	Fertility Rate	1.84	1.72	0.505	1.09	4.07	1.29	4.98
7	GDP Growth	2.88	2.99	4.21	-32.1	42.4	-0.630	15.9

Summary statistics of retained indicators of demographic, labour market, and migration.

4.1.2. Labour Force Participation Rate by Age Group

Figure 4.1.2: Distribution of EU Labour Force Participation Rate by Age Group

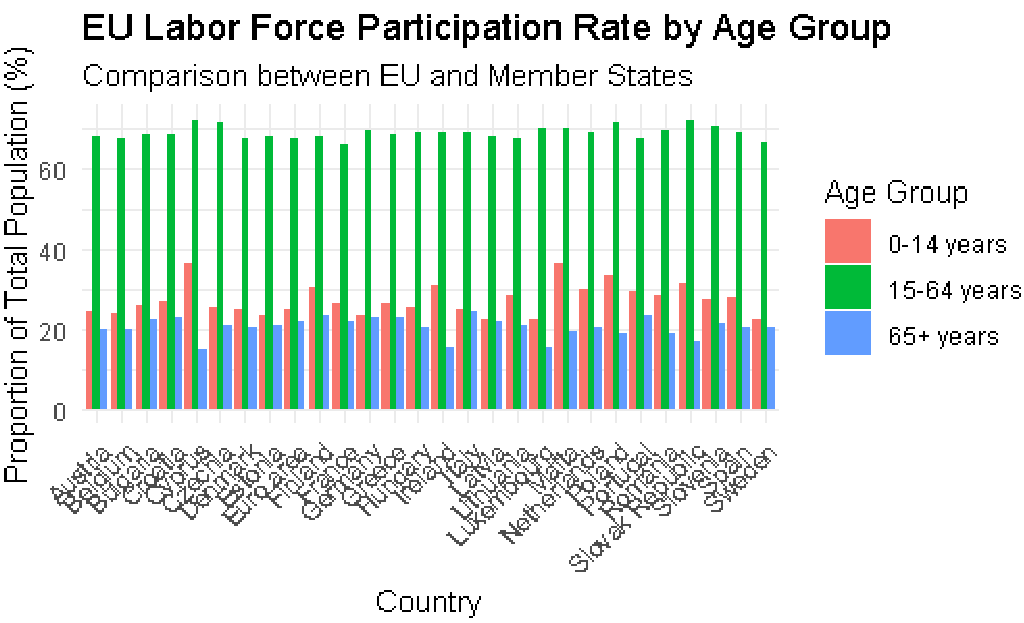


Table 4.1.1 provides a summary of selected indicators related to migration, labour market dynamics, and demographic ageing throughout the European Union. And Figure 4.1.2 compares the labour force participation rate across three age groups (0–14, 15–64, and 65+) within the EU. These visualisations help capture structural differences in labour force dynamics across the EU. From

Table 4.1.1, we can see that the labour force participation rate (LFPR) in the context of the EU is quite close to that of a classical normal distribution (skewness = 0.187). EU member states generally have an above-average rate of labour force participation (57.5%), and the variance among them is not alarming (SD = 6.70). However, overlaying the statistics with information from Figure 4.1.2 reinforces the idea that the engagement level of the EU population aged 15 and older appears consistent in relative terms, suggesting that demographic ageing is a significant labour market concern for EU member states. Both graphics stress the need for migrant-friendly policies to attract working-aged migrants, which can help mitigate workforce gaps and sustain economic productivity in the EU sustainably.

4.1.3. EU Employment Rate Distribution by Age Group

According to Table 4.1.1, in terms of their general descriptive statistics, the employment-to-population ratio (EmpR) of the EU is quite comparable to that of its LFPR counterpart. Just like LFPR, the EmpR has a slightly above average level of employment (mean = 52.6%) with a moderate variability (SD = 6.22) across the EU. However, unlike LFPR, which has a positive skewness (0.187), EmpR has a negative skewness (-.0262). These characteristics make both indicators suitable proxy indicators of the labour market gap in the EU. The Emp-to-Population-Ratio has a smaller and negative skewness, which implies that a relatively small number of EU member states have a lower employment rate. Considering the absolute value of skewness, emp-to-pop is relatively more normally distributed in the EU, which makes it a better candidate as a proxy indicator of the labour market gap.

4.1.4. Distribution of EU-wide net migration among EU member states

Figure 4.1.3: Net migration distribution among EU member states

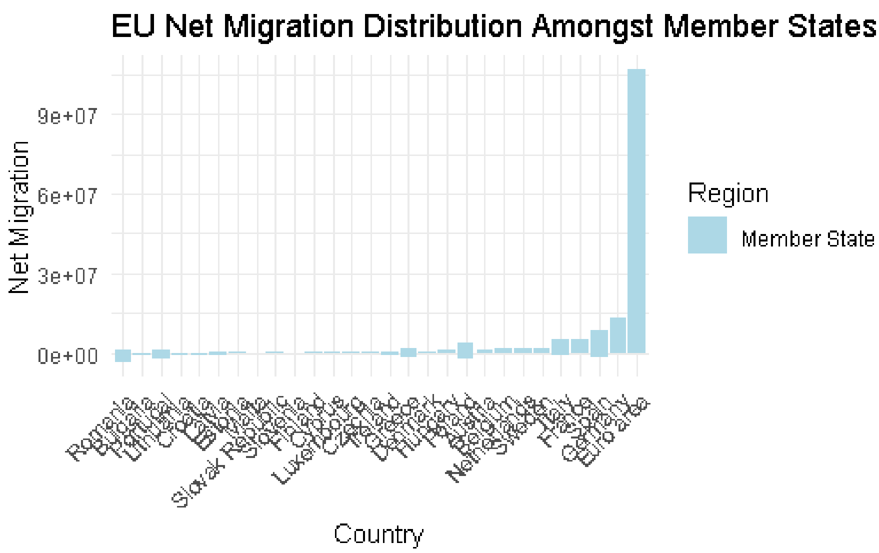
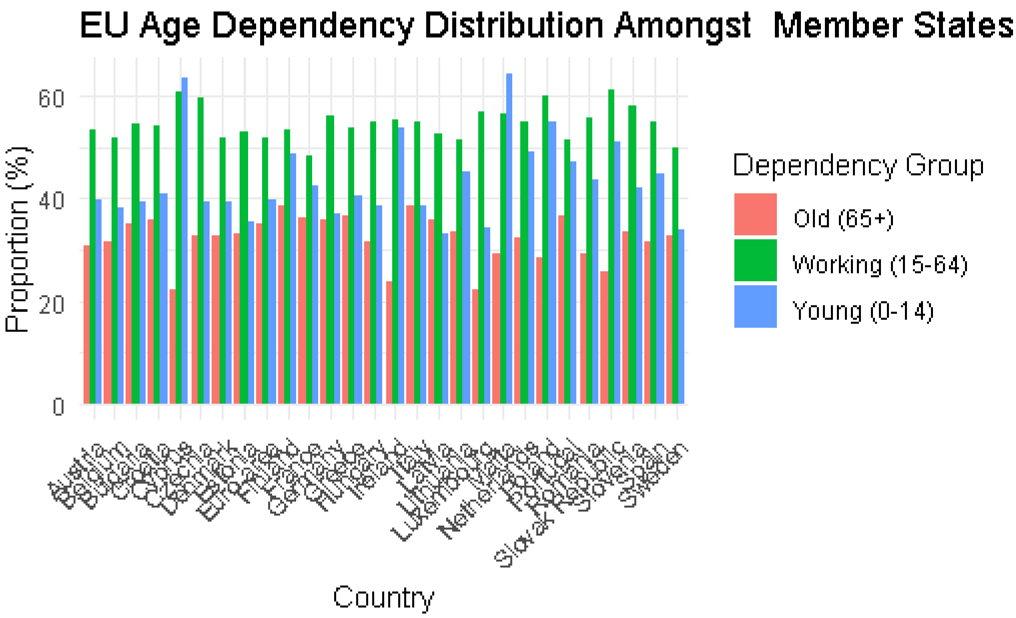


Figure 4.1.3 and Table 4.1.1 portray net migration as a highly skewed phenomenon across the EU. The statistical profile of net migration indicates a high positive skewness (7.65) and significant variability (SD = 170,435), along with a mean net migration of 39,910 and a median net migration of only 4,416. This picture generally tells that while a few EU member states, like Germany and Spain, receive or attract a disproportionately high number of migrants, others, like Slovakia, Hungary, and Bulgaria, receive a relatively low number, as shown in Figure 4.1.3. This reveals the uneven distribution of net migration across the EU and raises different policy challenges for the EU and EU member states. These results imply that, while migration has the potential to alleviate labour shortages caused by demographic ageing, its uneven allocation may limit its effectiveness across the EU. This indicates the need for EU policymakers to consider coordinated strategies to direct migration flows towards ageing regions with critical labour market gaps.

4.1.5. Age dependency distribution as a proportion of the EU population by age group

Figure 4.1.4: Age dependency distribution as a proportion of the population in different age groups



According to the results in Table 4.1.1, the mean age dependency ratio in the EU is 52.2, almost equal to the median age dependency ratio (52.5), with a moderate variability of ±5.7 points and a moderate skewness of 0.842. This indicates a generally ageing population with some variation across member states. Overall, this means that a relatively smaller number of EU member states have a dependency ratio that is higher than the EU average. In other words, it means that on average, 100 people of working age support 52.2 dependent children and elderly people combined. On the other hand, Figure 4.1.3 highlights a growing proportion of the population in the 65+ age group, especially in countries like Italy, Germany, and Greece, where dependency burdens are highest. This demographic shift signals mounting pressure on the working-age population and increasing fiscal strain on the EU economy in general. To mitigate these challenges, migration policies should prioritise attracting and integrating working-age migrants into the ageing sector of the EU economy. Such strategies can rebalance dependency ratios and sustain labour force participation rates, especially in countries facing the steepest demographic declines.

4.1.6. Age distribution amongst EU members by population and age group.

Figure 4.1.5: Age Distribution of EU Member States' Population by Age Group

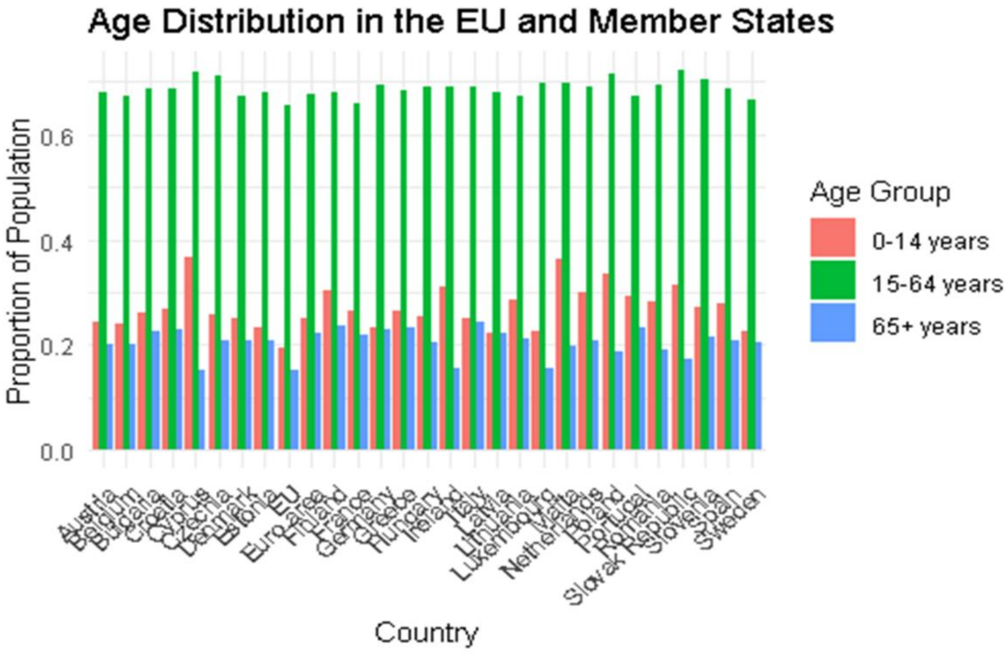


Table 4.1.1 shows the proportions of the elderly EU population (aged 65+), as opposed to Figure 4.1.2, which summarises the distribution of the EU population relative to three major age groups. According to the table, the mean proportion of the elderly EU population is 14.0, while its median proportion is 13.5; these values are quite close to each other, and the skewness of 0.376 suggests that the distribution is near a normal distribution. These statistics tell us that the proportion of the elderly population of the EU is around 13–15% of the total EU population. The table also indicates that the proportion of the elderly population ranges from 10.3% to 17.7%. This information is reinforced by Figure 4.1.2, which, besides showing the distribution of the elderly dependent population, equally shows the proportion of the different major age groups. This knowledge allows us to gain a comprehensive understanding of the distribution of the total dependent EU population across EU countries. Findings from both visuals help us to have an idea about how the trend of healthcare expenditure and pension cost advances as the different age groups evolve, especially the diminishing working-age population. This information has significant policy repercussions in the EU and its member states.

4.1.7. EU Fertility Distribution among EU Member States

Figure 4.1.6: EU Fertility Distribution among EU Member States

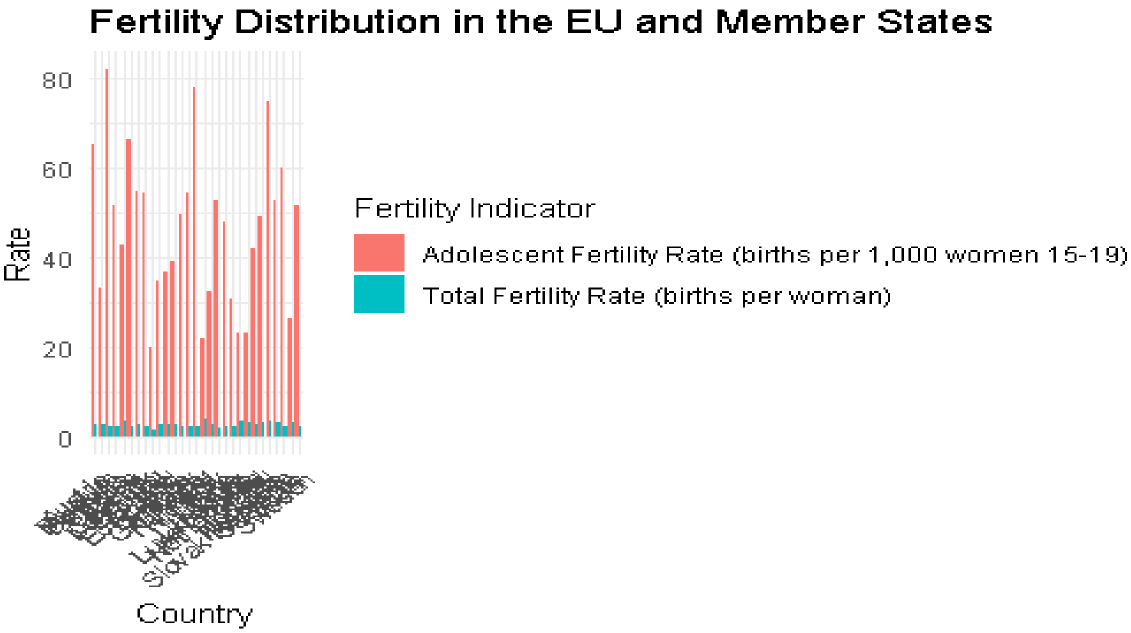


Table 4.1.1 and Figure 4.1.6 collectively describe the distribution of fertility among EU member states. Table 4.1.1 shows that the mean fertility rate among EU member states is 1.84 and ranges from 1.09 to 4.07; recent figures for 2025 even show it declining from 1.84 to 1.36 births. This value generally means that over the twelve-month period that preceded 2025, women of childbearing age in the EU have at most close to two children for the most fertile ones. A median fertility rate of 1.72 indicates that there are as many women whose fertility rate is below 1.72 as there are above; better still, it implies that 50% of women in the EU have a fertility rate of 1.72. The same table shows that the median fertility is less than the mean fertility, which, when combined with a skewness of 1.29, tells the story of a distribution with a positive skew. This implies that a few outlier member states (e.g., Bulgaria and France) have high fertility rates, while relatively more member states (e.g., Malta, Spain, and Lithuania) have fertility rates that taper below the replacement level of 2.1. Figure 4.1.6 reflects this fertility story, highlighting the EU's fertility inertia. One of the factors driving EU demographic ageing is its declining fertility, which has a knock-on effect on labour supply and economic sustainability. Migration offers a viable policy tool to mitigate these challenges. The skewness of the data shows that different EU member states will have different policy emphases or orientations depending on their specific condition.

4.1.8. EU GDP Growth Distribution Among EU Member States

Figure 2.7: EU GDP growth distribution among EU member states

As can be inferred from Table 4.1.1, the EU GDP growth rate has a wide disparity, ranging from a significant contraction (-32.1%) to strong economic expansion (42.4%), a substantial variability (SD = 4.21), with an asymmetric distribution (skewness = 1.29). These statistics suggest that while some EU member states have experienced a significant economic downturn, others have had considerable economic growth. A small number of EU member states have high GDP growth rates, while a relatively higher number of EU member states have experienced either modest or negative growth rates. These statistics suggest the following challenges: Negative economic growth highlights economic recessions, crises, or structural inefficiencies; low and negative economic growth highlights unemployment, reduced public revenues, and social instability, which are susceptible to influencing migrants' destinations among EU member states.

4.2. Results of Trend Analysis

Table 4.1.1. Snapshot of the Trends of Selected Years

	Variable	1990	2000	2010	2020	2023
1	**TPA_65_plus**	44622762	53225443	62448305	73483885	77497965
2	**total_pop**	3.16E+08	3.26E+08	3.4E+08	3.47E+08	3.5E+08
3	**OADR**	20.94	24.28	27.69	33.11	34.89
4	**LifExp**	74.7	77.08	79.63	80.43	81.41
5	**TFR**	1.54	1.47	1.58	1.48	1.38
6	**MgrStock**	23307163	29602637	43696432	40247491	46597534
7	**NMgr**	676023	673775	656784	1066639	1304104
8	**remittances**	0.46	0.41	0.63	0.82	0.82
9	**RefuPop**	1119086	1282432	1025628	2352865	5458655
10	**LFPR**	54.3	55.02	56.75	56.26	57.82
11	**EmpR**	NA	35.99	32.64	31.6	36.24
12	**gdp_pc_gr**	2.95	3.81	2.04	-5.65	0.21
19	**MgrStock_pct**	7.38	9.09	12.83	11.6	13.3

Table 4.1.1 captures the trend of selected EU-wide aggregates representing the performance indicators of demographic ageing, migration, and the labour market to reflect the general trend from 1990 through 2023. The total population aged 65+ (TPA_65_plus), old-age dependency ratio (OADR), labour force participation rate (LFPR), total fertility rate (TFR), and net migrant stock

(NMgr) are included to illustrate long-term trends relevant to the study of demographic ageing, migration, and labour market dynamics. The snapshot overtly shows a progressive trend for most of the indicators, which include a sustained increment of the elderly population, progressive amelioration of life expectancy, dwindling fertility rates, and ever-buoyant international remittances. However, some entries, like the share of the employment rate, have been omitted due to data limitations.

4.3. Results of Hypothesis Testing

4.3.1. Results of the Wald test for cointegration

Model	Residual DF	F	Pr(>F)
Full model	28		
Restricted model	33	4.2834	0.0051 **

4.3.2. Interpretation of the Results of the Wald Test for Cointegration

Table 4.3.1 summarises the results of the Wald test, here considered as a test for the existence of cointegration amongst the variables specified in the ARDL model. The confirmation of the existence of a long-term cointegrating relationship amongst the variables specified in the model is a condition sine qua non for this study's main purpose. In other words, the existence of cointegration is considered a precondition for testing the two hypotheses of this study. The Wald model's null hypothesis states that the coefficients of the lagged terms specified in the ARDL are equal to zero, which means they are not statistically significant and don't have any meaningful contribution in the ARDL model. As a result, when the coefficient of the lagged terms is equal to zero, it serves as evidence for the non-existence of a long-run relationship amongst the specified variables in the model. According to Table 4.3.1, the P-value of the joint coefficient is statistically significant (P-value 0.0051), which justifies the rejection of the null hypothesis of the Wald test. The rejection of the Wald test confirms the existence of at least one cointegrating relation in the specified ARDL model.

4.3.3. Results of the ARDL Model (Output of the ARDL Model)

Table 4.3.2 Output of the ARDL Model

4.3.4. Interpretation of the Output of the ARDL Model

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-4.192456	1.546477	-2.711	0.011329 *
L(log_LFPR, 1)	-0.724445	0.177053	-4.092	0.000328 ***
L(log_TPA_65_plus, 1)	0.491081	0.144629	3.395	0.002067 **
L(log_OADR, 1)	-0.527208	0.159007	-3.316	0.002537 **
L(log_NMgr, 1)	0.003023	0.001669	1.812	0.080771.
L(log_remittances, 1)	0.090934	0.030621	2.970	0.006054 **
d(log_TPA_65_plus)	0.678787	0.454923	1.492	0.146857
d(log_OADR)	-0.809352	0.280805	-2.882	0.007501 **
d(log_NMgr)	0.002307	0.001125	2.051	0.049774 *
d(log_remittances)	0.020669	0.046839	0.441	0.662401

Table 4.3.2 summarises the output of the ARDL model, which was used to test the hypothesis of the current dissertation, as already explained in Chapter Three. The model captures the hypothesised relationship between labour force participation rate (LFPR), here considered as the outcome variable, and the explanatory variables, which include TPA_65_plus (population aged 65+), OADR (old age dependency ratio), NMgr (net migration), and remittances with lags allowed.

As already mentioned, all the variables in the model have been transformed into their respective differenced log-levels and their associated lags to capture both the long- and short-run dynamics of the modelled relationship. The coefficient of the differenced log-level is the short-run coefficient and captures the immediate effect of the explanatory variables, while the coefficient of the log-level captures the long-run contribution of the variable if and only if cointegration has been established through either a bound test or the Wald test, as is the case in the current study. The coefficient of the log-level of the dependent variable (L(log_LFPR, 1)) is referred to as the error correction term (ECT), and when its value is negative and significant, it indicates stability and convergence of the model to equilibrium when it temporarily deviates from equilibrium.

In the ARDL model, the null hypothesis assumes that there is no significant effect on the dependent variable ($\beta j = 0$) of the model. As can be inferred from the results, the p-values of the coefficients of L(log_TPA_65_plus, L(log_OADR, 1), L(log_remittances, 1), d(log_OADR), and d(log_NMgr)) are statistically significant at least at the 5 percent level of significance. This generally implies the existence of both immediate effects and long-term contributions to the concerned variables. More specifically, the coefficient of d(log_OADR) is significant and negative, which indicates that an increase in old age dependency is associated with a reduction of LFPR in the short run. Similarly, the coefficient of d(log_NMgr) is significant and positive, implying that an increase in net migration in the EU is associated with an increase in LFPR in the short term. The coefficient of the ECT in this case is -0.73, implying that about 75% of the deviations of the equilibrium are corrected annually. The coefficients of the differenced log-levels of TPA and remittances are not statistically significant, which means that they don't have any immediate effect on LFPR in the short term within the context of the EU. The results also show that the F-statistic of the model is statistically significant with an R-squared value of 0.65, which implies that the ARDL model captures about 65% of the variation, which is quite a good fit in the context of time series data.

Chapter 5: Discussion of major findings

5.1. Overview

This chapter critically discusses major findings from the literature study and quantitative analysis. Most importantly, it introduces an ecosystem of three frameworks conceptualised and developed within the context of this dissertation to optimise the role of migration in addressing the ageing EU labour market challenges:

I. The Ageing Economy Challenge framework (AEC-Mix)
II. The Migrant-Led Labour Gap Adjustment Framework (ML-GAF), and
III. The Barrier Adjustment Framework for Migrant Labour Access (BAF-MLA).

These frameworks collectively emerged as a toolkit for identifying and prioritising ageing economy challenges, enhancing the role of migration in responding to them, and dismantling implementation barriers.

5.2. Major Findings Highlighted and Put into Perspective

This study critically examined the extent to which migrant labour can mitigate labour market dynamics by hypothesising that demographic ageing increases labour market gaps and that migration reduces labour market gaps caused by demographic ageing in the context of the EU. Results from the literature study and quantitative analysis generally support these hypotheses. Literature findings indicate that demographic ageing hinders labour market dynamics, which converges with the results of quantitative analysis.

Based on the results of quantitative analysis, the coefficients of the log-level and differenced log-levels specified in the ARDL model are statistically significant, which indicates the existence of both immediate and long-term contributions of migration, demographic ageing, and labour market participation in a cointegrated system of equations. The results of the VECM, intended to further investigate the perceived bidirectional nature of the relationships, showed the existence of three cointegrated relationships. However, the bidirectionality could not be made more conclusive because of data requirement limitations imposed by the VECM. Compared to the ARDL model, which could be implemented with only 40 annual observations, the VECM requires more observations to generate the necessary statistical power required to test for bidirectionality.

Findings from the univariate analysis generally show that indicators of migration, demographic ageing, and labour market dynamics are skewed, which indicates that the drivers of demographic ageing are not homogenous in many respects.

Consequently, there is no one-size-fits-all solution to address EU-wide demographic ageing challenges. However, EU aggregates could serve as benchmarks for comparison across the EU member states. The main demographic indicators (TPA 65+ and OADR) are more stable with an increasing trend and could grow worse because their core drivers, such as life expectancy at birth, keep improving while fertility rates are constantly below the EU replacement level. Ageing patterns vary considerably across Member States, with countries such as Italy, Germany, and Greece facing a more acute demographic old-age dependency ratio, while others, including Ireland and Luxembourg, experience comparatively younger population structures (Eurostat, 2024). These disparities have important implications for policy design, and this is where our proposed ecosystem of three frameworks can provide support to the EU policy-making process at all levels of the migration solution hierarchy (strategy, policy, programmes, and projects) illustrated in Figure 5.2. At the level of the EU, the EU-wide policy strategy should be anchored on coordination, resource allocation, and the facilitation of intra-EU mobility, without undermining the possibility of targeted state-level interventions to correct perceived or anticipated labour shortages or excesses (Lutz, 2019).

Our proposed AEC-Mix framework is conceptualised to inform and facilitate the migration strategy formulation phase. At the member state level, our proposed ML-GAP framework is conceptualised to support the formulation of sectoral migration policy and specific policy levers or instruments informed by country/sectoral needs, current or perceived patterns, and socio-cultural priorities as noted in the European Commission (2020). At the operational level, a migration-orientated programme or project, depending on the scale and spatial allocation, could be at the EU level or the member state level. The BAF-ML framework is conceptualised to dismantle institutional and structured challenges to migrant employment across the EU. Our solution ecosystem is conceptualised to enable multi-level management of labour market dynamics such that the EU will focus on the elaboration of common objectives in a way that will allow for the operationalisation of migration interventions in response to labour market challenges that are flexible enough for local conditions.

The EU labour market, the Dublin regulatory system, and EU members' national policies, by virtue of their inert conceptual foundation, necessarily result in the inefficient allocation of migrants' labour in the EU labour market. While the labour market mechanism relies on the invisible hands of demand and supply of migrant labour to attain economic efficiency, the Dublin system relies on the principle of the first point of irregular entry, recent possession of a visa/residence permit, and family presence to prevent "asylum shopping". Yet, the policy authority of EU member states uses national/political economic objectives to achieve national interests/goals, sometimes subject to lobbying interests, which could explain why some data-driven solutions are sometimes downplayed. The interplay of these opposing forces leads to the inefficient allocation of migrant labour in the EU labour market. The resulting misallocation sometimes places labour in a spatial or sectoral location that does not necessarily correspond to the optimum labour market placement required to achieve labour market efficiency due to labour mismatch. For instance, in the spirit of the Dublin system, a refugee from Syria entering the EU via Italy would be required to engage with Italy's labour market, which might have already been saturated (surplus) or have minimal labour market integration programmes, whereas that same labour would be highly needed in Germany with a relatively higher demand, thus leading to inefficient allocation of migrant labour within the EU labour market in general. Quite similarly, Eastern/Central European countries activate their national policy instruments and choose to absorb far less migrant labour than their labour market might require to attend to labour market efficiency. These scenarios call for an improved coordination mechanism between the EU and member states.

Overall, this study's results show that migration is a crucial component in responding to the EU's ageing economy challenges. It equally highlights other competing solutions, such as technological improvements within the context of AI and the robotisation of traditional tasks in many industries. However, according to (Antón et al., 2023), robotisation may increase work intensity without necessarily upgrading job quality in physically demanding jobs in agriculture and the elderly healthcare sectors, where migrant labour is highly sought after. Similarly, (Hundt, 2024) admits that while AI can practically replace human labour in white-collar jobs and in routine administrative functions, such is not the case in sectors that are physically intense and socially complex. Reuters (2025) even notes that the high cost, safety concerns, and technological constraints associated with AI and robotisation options are susceptible to delaying their wide implementation, at least in the horizon of 2030. In light of the above limitations akin to AI and robotisation, it might be more reasonable to integrate them into the migration solution rather than consider them as a full substitute. The current study's major focus is on migration, as it centres on human capital and equally provides three solution frameworks, which are expected to enhance the role of migration in responding to ageing economy challenges in the EU.

5.3. Proposed Solution Set: Ecosystem of three frameworks

5.3.1. The Ageing Economy Challenge framework (AEC-Mix)

The AEC-Mix is primarily conceptualised to serve as a holistic diagnostic tool to support the identification and prioritisation of major ageing economic challenges. It's composed of four major interrelated tools, each focusing on demographic ageing-induced challenges. Through a specific matrix (grid) and associated matrices, it captures country-level indicators and enables EU aggregation required for monitoring and evaluating performance across time and space. Each tool conveniently translates into a specific set of questions for data collection and associated actionable dimensions with policy and budgetary implications. This makes the AEC-Mix framework a holistic tool for identifying, quantifying, and prioritising the economic impact of demographic ageing in a systematic and structured manner. The fundamental idea and finding that enabled its development stem from this study's desire to cluster and compartmentalise gaps and themes that emerged in EU-based studies that link migration to age-induced labour market gaps. The literature study led to the mapping, categorisation, and quantification of gaps in the literature.

The AEC-Mix has a consistent logic; it is scalable, adaptable, practical, simple, comprehensive, data-driven, and theoretically grounded. For instance, its demographic tool helps analyse the core drivers of demographic ageing by asking relevant questions related to fertility, longevity, migration, and spatial imbalance in terms of the rural-urban divide in the EU age distribution. The labour market dimension helps to analyse labour market dynamics and capture workforce challenges, while the fiscal mix tool helps to evaluate the economic sustainability of the ageing economy, and the policy mix tool helps to analyse the governance and intervention structure of the EU and those of its member states to enable concrete and institutionalised actions.

AEC Framework Visualised

```
[EU Ageing Economy Challenges]
│
├── **Demographic Mix** → Fertility, Longevity, Migration, Spatial Allocation
├── **Labour Mix** → Sectoral Shortages, Skill-Set Mismatch, Productivity Slowdown
├── **Fiscal Mix** → Pension system strain, healthcare cost, tax base erosion
└── **Policy Mix** → Legal barriers. Political resistance, coordination failure
```

5.3.2. The Migrant-Led Labour Gap Adjustment Framework (ML-GAF)

The main purpose of the ML-GAF framework is to optimise migrant labour at the operational level by first mapping their profiles and aligning them with age-induced EU labour market needs in specific sectors and spatial allocations. It's conceived to have five actionable dimensions, which include identification of the demographic fit, migrant skill-set matching, migrant spatial distribution allocation, and policy leverage. Ideally, its application should proceed from the results of the AEC-Mix analysis; however, it doesn't matter which approach has been used to identify an ageing economy challenge. For instance, findings from our literature study reveal that the most outstanding demographic ageing-induced challenge in the EU is the labour market gap, which accounts for over 26% of the gaps identified through the literature studied. The EU and its member states can use the logic of the ML-GAF to systematically resolve labour market challenges, gauge their evolution and, by implication, improve overall EU dependency ratios in the medium and long term.

ML-GAF—Framework Visualised

```
[EU Ageing Labour Gaps]
│
├── **Demographic Fit** → Age (25–54 yrs), Fertility (TFR differentials)
│
├── **Skill Matching** → Hard Skills (Healthcare, STEM), Soft Skills (Language B1+)
│
├── **Spatial Distribution** → Urban-Rural Allocation, Regional Incentives
│
├── **Policy Leverage** → Visa Fast-Tracks (EU Blue Card), Retention Bonuses
│
└── [Output: Reduced Dependency Ratios]
```

5.3.3. Barrier Adjustment Framework for Migrant Labour Access (BAF-MLA)

The main purpose of the BAF-MLA framework is to identify and dismantle structural and institutional barriers to migrant formal employment and to ease their full participation in the EU labour market. This would enable them to contribute more in the formal labour sector and, by implication, help to reduce their participation in the illegal or underground economy and expand the tax base. As can be inferred from the flowchart below, the BAF-MLA consists of five tools that enable the formulation of specific questions and data collection points for specific metrics. For instance, this study equally found that although migration has a legitimate potential to respond to age-induced labour market gaps, migrants are constrained by numerous barriers to their full employment. The BAF-MLA framework is a comprehensive toolkit for analysing barriers to labour market access and dismantling them.

BAF-Framework Visualised

[Migrant Employment Barriers]

```
├── **Legal/Admin** → Complex Visas, Residency Rules → Fix: Fast-Track Recognition
├── **Human Capital** → Language, Skill Gaps → Fix: Bundled Training (Language + Credentials)
├── **Institutional** → Policy Fragmentation → Fix: One-Stop-Shop Hubs
├── **Discrimination** → Hiring Bias → Fix: Anonymous CVs
├── **Spatial/Sectoral** → Urban-Rural Mismatches → Fix: Relocation Grants
└── [Output: Higher Employment Rates]
```

Figure 5.2: Strategic Operational Hierarchy for responding to ageing EU labour market gaps

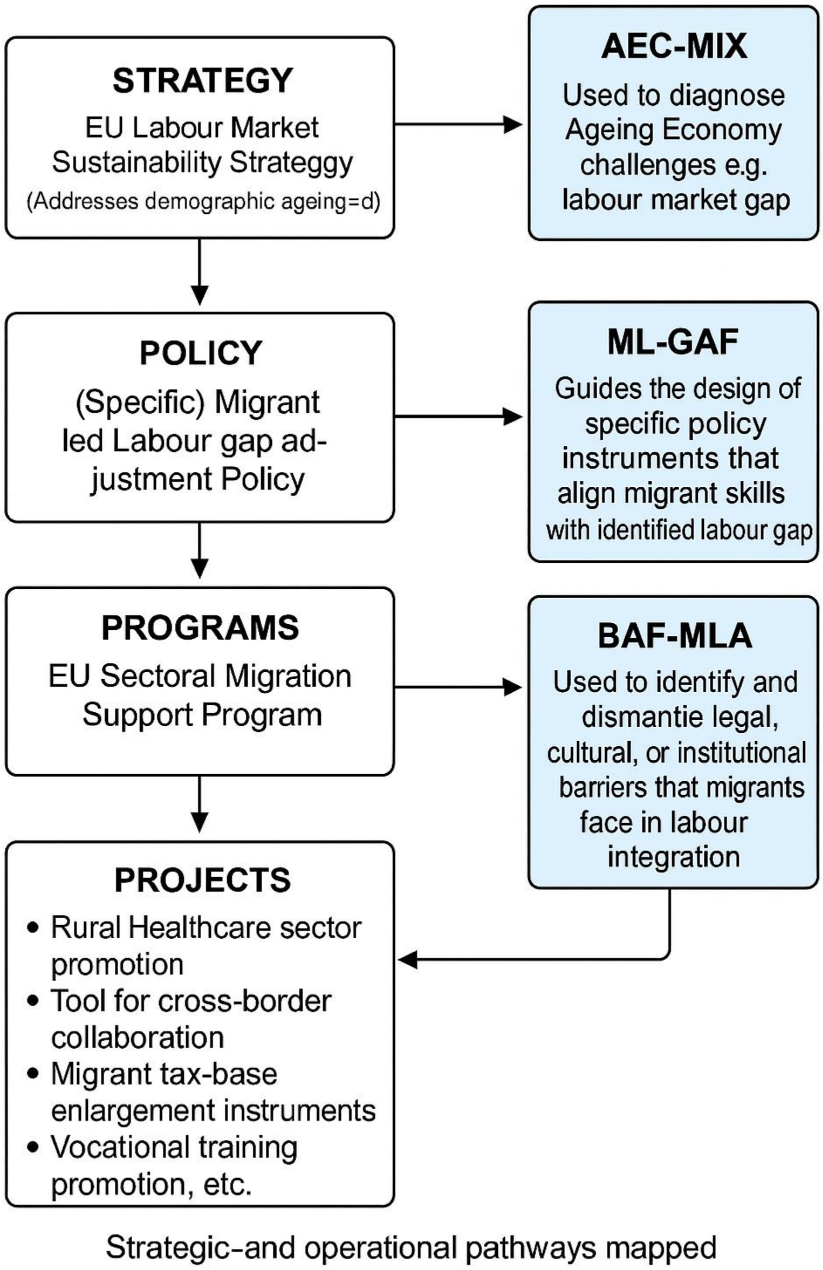


Figure 5.2 illustrates a multi-level framework that translates our empirical findings into a coherent strategy-policy-programme-project structure. The AEC-MIX framework informs high-level strategy through diagnostics of prioritised ageing economy challenges (e.g., labour market gaps). The ML-GAP framework supports the design of policy levers or policy instruments that align migrant skill sets with EU sectoral and spatial labour demands. The BAF-ML framework guides programme or project-level implementation by identifying and dismantling structural barriers to migrant employment in the EU labour market.

6. Conclusion

6.1 Overview

This dissertation sought to appraise the extent to which migration may be a sustainable solution to the challenges of the greying EU economy and to demonstrate how migration can be optimised as a sustainable policy logic through the proposal of an innovative ecosystem of three frameworks. In this chapter, we directly address the purpose of this dissertation and answer the main research question, while highlighting the value addition of our solution set, reflecting on its limitations.

6.2. Answers to Research Objectives

Research Purpose: Does migration have a legitimate potential to address labour market challenges associated with demographic ageing within the context of the EU?

Yes. This study demonstrates that migration plays a significant role in addressing the challenges of the ageing EU economy, based on its findings from the literature study, results of the quantitative analysis, and the cumulative impact of its proposed ecosystem of three frameworks. Through the Ageing Economy Challenge framework (AEC-Mix), this study diagnoses six major EU ageing economy challenges and notes that the labour market gap challenge is the most outstanding challenge. Through the Migrant-Led Labour Gap Adjustment Framework (ML-GAF), this study demonstrates how migrant labour can be optimised in the EU labour market. And finally, through the Barrier Adjustment Framework, this study shows how obstacles to migrants' labour force participation in the EU labour market can be identified and dismantled. In conclusion, this study has sufficiently shown that migration not only has the potential to address EU labour market challenges, but it also has the potential to address other major ageing economy challenges currently faced by the EU/EU member states.

The main research question: “To what extent can migration mitigate labour market challenges associated with demographic ageing in the EU?"

This study has demonstrated that by using the different frameworks and tools in its solution ecosystem, the EU and its member states can effectively adopt this study's solution set to analyse, diagnose, and prioritise region/country-specific ageing economy challenges and urgently activate appropriate solutions to address each challenge. Consequently, the migration can help mitigate labour market challenges to a significant level, and the extent can be enhanced with our proposed ecosystem of frameworks. However, the extent to which results can be achieved is elastic and contingent on other factors, including the political will of the EU and its member states and other factors related to geopolitics, political economy, global climate and environmental change, and the global financial system, not leaving out global peace and technological advancement.

6.3. Summary of Implications and Recommendations

The frameworks can be used independently and collectively in migration policy, programmes, and project management in general. For instance:

- The elaboration of actionable roadmaps for EU migration management and control.

- Monitoring and evaluation of migration policy and programmes over time and space.

- As a lobbying tool to streamline the visa process between the EU/EU member states and partners.

- As a tool for cross-border collaboration amongst EU member states

- As a tool for predicting labour market gaps and analysing the potential of migration corridors.

6.4. Reflection & Limitations

Although the framework makes substantial contributions in dealing with the ageing EU labour market challenges, some of its major limitations are worth mentioning. While the frameworks are holistic, data-driven, policy-aligned, and dynamically adaptable, they have not yet undergone longitudinal testing. Their implementation across the EU or within EU member states will necessitate adequate coordination capacity across relevant EU or national ministerial departments to deal with potential conflict between EU-wide priorities and those of EU member states in general. Each framework's performance relies on the utilisation of high-quality data and a consistent stream of data flow. For instance, ML-GAF may be limited by a lack of accurate data on undocumented migrants in the agricultural sector, which may limit migrant profiling and matching in the agricultural sector. The frameworks are developed through 20 EU-based studies, which could potentially limit their generalisation and application in other contexts if context-specific considerations are not factored in. Cultural barriers in some ageing societies, like the rural eastern EU, may create resistance to migration and generate populist narratives that could undermine the adoption of the frameworks.

As the challenges associated with EU migration and demographic ageing continue to evolve, the proposed framework is designed to help tackle these challenges by providing useful insights and practical response tools and solutions. While looking forward to testing the proposed frameworks, together they serve as a toolkit for scholars, professionals, and researchers to identify, prioritise, tackle, monitor, and evaluate ageing economy challenges and to optimise the role of migrants in the EU economy.

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Appendices

Appendix _1: Table 3.2.1: List of most relevant variables considered in the analysis

Indicators	S/N	Specific variable names	Shorten Names	No. of observations
A. Demographic Ageing	**1.1**	Population 65+ (% of total pop)	TPA_65_plus	63
	1.2	Old-age dependency ratio	OADR	63
	1.3	Life expectancy at birth	LifExp	63
	1.4	Total Fertility Rate	TFR	63
	1.5	Total annual EU population	total_pop	63
B. Migration	2.1	Migrant stock	MgrStock	33
	2.2	Net migration	NMgr	64
	2.3	net_migration_rate	NMgrR	33
	2.4	Remittances	remittances	49
	2.5	refugee_pop	RefuPop	34
C. Labour Market	3.1	Labour force participation rate	LFPR	41
	3.2	Employment-to-population ratio	EmpR	34
	3.3	Unemployment rate		34
D. Economic Context	4.1	gdp_per_capita_growth	gdp_pc_gr	63
E. Sector-Specific	5.1	Employment in agriculture	emp_agri	33
	5.2	Employment in industry	emp_ind	33
	5.3	Employment in services	emp_serv	33

	5.4	Health expenditure (% of GDP)	health_exp	33
	5.5	sector_services_share	serv_share	33
	5.6	sector_industry_share	ind_share	33
		health_exp_per_elderly	exp_elderly	33

Appendix_2: Table 3.2.3: Explained Variance by Component

Result of Principal Component Analysis (PCA) Explained.

Table 3.2.3: Explained Variance by Component

Principal Component	Explained Variance (%)	Cumulative Variance (%)
PC1	65.12	65.12
PC2	22.65	87.77
PC3	7.47	95.24
PC4	3.97	99.21
PC5	0.79	100.0
PC6	0.0	100.0

Table 3.2.4: Variable Contributions to PC1 and PC2

Variable	PC1 Loading	PC2 Loading
TPA_65_plus	-0.296	0.026
OADR	-0.293	0.043
LifExp	-0.297	-0.047
TFR	0.096	-0.435
MgrStock	-0.265	-0.088
NMgr	-0.183	-0.002
remittances	-0.292	-0.101

RefuPop	-0.207	0.355
LFPR	-0.267	0.077
EmpR	0.093	0.473
gdp_pc_gr	0.173	0.135
emp_agri	0.297	0.055
emp_ind	0.293	0.1
emp_serv	-0.296	-0.081
health_exp	-0.005	-0.489
serv_share	-0.296	-0.081
exp_elderly	0.193	-0.386

Appendix_3: Table 3.2.2: Correlation matrix table

	Variable1	Variable2	Correlation
87	serv_share	emp_serv	1.0000000
97	emp_serv	serv_share	1.0000000
2	OADR	TPA_65_plus	0.9979569
19	TPA_65_plus	OADR	0.9979569
15	emp_agri	total_pop	-0.9968484
61	total_pop	emp_agri	-0.9968484
77	emp_serv	emp_ind	-0.9916500
86	emp_ind	emp_serv	-0.9916500
78	serv_share	emp_ind	-0.9916500
96	emp_ind	serv_share	-0.9916500
18	serv_share	total_pop	0.9872803
90	total_pop	serv_share	0.9872803
17	emp_serv	total_pop	0.9872803
80	total_pop	emp_serv	0.9872803
45	emp_serv	remittances	0.9872541
83	remittances	emp_serv	0.9872541
46	serv_share	remittances	0.9872541
93	remittances	serv_share	0.9872541
68	serv_share	emp_agri	-0.9824419
95	emp_agri	serv_share	-0.9824419
67	emp_serv	emp_agri	-0.9824419
85	emp_agri	emp_serv	-0.9824419
44	emp_ind	remittances	-0.9788849
73	remittances	emp_ind	-0.9788849
36	emp_serv	LifExp	0.9783792
82	LifExp	emp_serv	0.9783792
37	serv_share	LifExp	0.9783792
92	LifExp	serv_share	0.9783792
13	remittances	total_pop	0.9779282
39	total_pop	remittances	0.9779282
32	remittances	LifExp	0.9766577
41	LifExp	remittances	0.9766577
35	emp_ind	LifExp	-0.9738646
72	LifExp	emp_ind	-0.9738646
1	total_pop	TPA_65_plus	0.9702103
10	TPA_65_plus	total_pop	0.9702103
43	emp_agri	remittances	-0.9701015
64	remittances	emp_agri	-0.9701015
6	emp_agri	TPA_65_plus	-0.9649086

```
60 TPA_65_plus    emp_agri  -0.9649086
12      LifExp   total_pop   0.9636457
30   total_pop      LifExp   0.9636457
16     emp_ind   total_pop  -0.9604410
70   total_pop     emp_ind  -0.9604410
4  remittances TPA_65_plus   0.9572253
38 TPA_65_plus remittances   0.9572253
8     emp_serv TPA_65_plus   0.9564574
79 TPA_65_plus    emp_serv   0.9564574
9   serv_share TPA_65_plus   0.9564574
89 TPA_65_plus  serv_share   0.9564574
34    emp_agri      LifExp  -0.9559131
63      LifExp    emp_agri  -0.9559131
11        OADR   total_pop   0.9528169
20   total_pop        OADR   0.9528169
66     emp_ind    emp_agri   0.9501789
76    emp_agri     emp_ind   0.9501789
25    emp_agri        OADR  -0.9469011
62        OADR    emp_agri  -0.9469011
22 remittances        OADR   0.9432180
40        OADR remittances   0.9432180
27    emp_serv        OADR   0.9393801
81        OADR    emp_serv   0.9393801
28  serv_share        OADR   0.9393801
91        OADR  serv_share   0.9393801
7      emp_ind TPA_65_plus  -0.9310215
69 TPA_65_plus     emp_ind  -0.9310215
3       LifExp TPA_65_plus   0.9168162
29 TPA_65_plus      LifExp   0.9168162
26     emp_ind        OADR  -0.9149370
71        OADR     emp_ind  -0.9149370
54    emp_agri        LFPR  -0.9121517
65        LFPR    emp_agri  -0.9121517
14        LFPR   total_pop   0.9090457
50   total_pop        LFPR   0.9090457
33        LFPR      LifExp   0.8970723
52      LifExp        LFPR   0.8970723
21      LifExp        OADR   0.8962312
31        OADR      LifExp   0.8962312
57  serv_share        LFPR   0.8881258
94        LFPR  serv_share   0.8881258
56    emp_serv        LFPR   0.8881257
84        LFPR    emp_serv   0.8881257
55     emp_ind        LFPR  -0.8533245
74        LFPR     emp_ind  -0.8533245
42        LFPR remittances   0.8532237
53 remittances        LFPR   0.8532237
5         LFPR TPA_65_plus   0.8197332
49 TPA_65_plus        LFPR   0.8197332
24        LFPR        OADR   0.7870873
51        OADR        LFPR   0.7870873
48 exp_elderly     RefuPop  -0.7746948
98     RefuPop exp_elderly  -0.7746948
58     emp_ind        EmpR   0.7256447
75        EmpR     emp_ind   0.7256447
59  health_exp        EmpR  -0.7203224
88        EmpR  health_exp  -0.7203224
23     RefuPop        OADR   0.7165585
47        OADR     RefuPop   0.7165585
```

Compact Correlation Matrix

The table below presents a compact summary of pairwise Pearson correlation coefficients between variables. Only unique pairs are shown to avoid redundancy.

Variable 1	Variable 2	Correlation Coefficient
TPA_65_plus	OADR	1.0

TPA_65_plus	LifExp	0.96
TPA_65_plus	TFR	-0.42
TPA_65_plus	MgrStock	0.79
TPA_65_plus	NMgr	0.56
TPA_65_plus	remittances	0.96
TPA_65_plus	RefuPop	0.74
TPA_65_plus	LFPR	0.82
TPA_65_plus	EmpR	-0.26
TPA_65_plus	gdp_pc_gr	-0.67
TPA_65_plus	emp_agri	-0.97
TPA_65_plus	emp_ind	-0.94
TPA_65_plus	emp_serv	0.96
TPA_65_plus	health_exp	0.01
TPA_65_plus	serv_share	0.96
TPA_65_plus	exp_elderly	-0.66
OADR	LifExp	0.94
OADR	TFR	-0.46
OADR	MgrStock	0.76
OADR	NMgr	0.56
OADR	remittances	0.95
OADR	RefuPop	0.76
OADR	LFPR	0.79
OADR	EmpR	-0.23
OADR	gdp_pc_gr	-0.67
OADR	emp_agri	-0.96
OADR	emp_ind	-0.92
OADR	emp_serv	0.94
OADR	health_exp	-0.01
OADR	serv_share	0.94

OADR	exp_elderly	-0.68
LifExp	TFR	-0.19
LifExp	MgrStock	0.93
LifExp	NMgr	0.59
LifExp	remittances	0.97
LifExp	RefuPop	0.61
LifExp	LFPR	0.9
LifExp	EmpR	-0.4
LifExp	gdp_pc_gr	-0.51
LifExp	emp_agri	-0.98
LifExp	emp_ind	-0.99
LifExp	emp_serv	0.99
LifExp	health_exp	0.08
LifExp	serv_share	0.99
LifExp	exp_elderly	-0.58
TFR	MgrStock	0.04
TFR	NMgr	-0.23
TFR	remittances	-0.18
TFR	RefuPop	-0.86
TFR	LFPR	-0.24
TFR	EmpR	-0.69
TFR	gdp_pc_gr	0.23
TFR	emp_agri	0.23
TFR	emp_ind	0.11
TFR	emp_serv	-0.16
TFR	health_exp	0.72
TFR	serv_share	-0.16
TFR	exp_elderly	0.81
MgrStock	NMgr	0.55

MgrStock	remittances	0.85
MgrStock	RefuPop	0.43
MgrStock	LFPR	0.94
MgrStock	EmpR	-0.43
MgrStock	gdp_pc_gr	-0.26
MgrStock	emp_agri	-0.88
MgrStock	emp_ind	-0.93
MgrStock	emp_serv	0.91
MgrStock	health_exp	0.07
MgrStock	serv_share	0.91
MgrStock	exp_elderly	-0.48
NMgr	remittances	0.61
NMgr	RefuPop	0.29
NMgr	LFPR	0.54
NMgr	EmpR	-0.26
NMgr	gdp_pc_gr	-0.19
NMgr	emp_agri	-0.56
NMgr	emp_ind	-0.55
NMgr	emp_serv	0.55
NMgr	health_exp	-0.06
NMgr	serv_share	0.55
NMgr	exp_elderly	-0.37
remittances	RefuPop	0.54
remittances	LFPR	0.78
remittances	EmpR	-0.51
remittances	gdp_pc_gr	-0.64
remittances	emp_agri	-0.98
remittances	emp_ind	-0.98
remittances	emp_serv	0.98

remittances	health_exp	0.22
remittances	serv_share	0.98
remittances	exp_elderly	-0.47
RefuPop	LFPR	0.66
RefuPop	EmpR	0.44
RefuPop	gdp_pc_gr	-0.34
RefuPop	emp_agri	-0.62
RefuPop	emp_ind	-0.53
RefuPop	emp_serv	0.57
RefuPop	health_exp	-0.61
RefuPop	serv_share	0.57
RefuPop	exp_elderly	-0.96
LFPR	EmpR	-0.11
LFPR	gdp_pc_gr	-0.22
LFPR	emp_agri	-0.86
LFPR	emp_ind	-0.86
LFPR	emp_serv	0.87
LFPR	health_exp	-0.23
LFPR	serv_share	0.87
LFPR	exp_elderly	-0.72
EmpR	gdp_pc_gr	0.35
EmpR	emp_agri	0.39
EmpR	emp_ind	0.49
EmpR	emp_serv	-0.45
EmpR	health_exp	-0.87
EmpR	serv_share	-0.45
EmpR	exp_elderly	-0.49
gdp_pc_gr	emp_agri	0.65
gdp_pc_gr	emp_ind	0.55

gdp_pc_gr	emp_serv	-0.6
gdp_pc_gr	health_exp	-0.48
gdp_pc_gr	serv_share	-0.6
gdp_pc_gr	exp_elderly	0.09
emp_agri	emp_ind	0.98
emp_agri	emp_serv	-0.99
emp_agri	health_exp	-0.14
emp_agri	serv_share	-0.99
emp_agri	exp_elderly	0.55
emp_ind	emp_serv	-1.0
emp_ind	health_exp	-0.18
emp_ind	serv_share	-1.0
emp_ind	exp_elderly	0.49
emp_serv	health_exp	0.16
emp_serv	serv_share	1.0
emp_serv	exp_elderly	-0.52
health_exp	serv_share	0.16
health_exp	exp_elderly	0.74
serv_share	exp_elderly	-0.52

Correlation Analysis by Variable Group

Demographic Ageing Variables

Variable 1	Variable 2	Correlation
TPA_65_plus	OADR	1.00
TPA_65_plus	LifExp	0.92
TPA_65_plus	TFR	-0.09
TPA_65_plus	health_exp	0.46
TPA_65_plus	exp_elderly	-0.50
OADR	LifExp	0.90

OADR	TFR	-0.15
OADR	health_exp	0.44
OADR	exp_elderly	-0.51
LifExp	TFR	0.20
LifExp	health_exp	0.50
LifExp	exp_elderly	-0.38
TFR	health_exp	0.52
TFR	exp_elderly	0.60
health_exp	exp_elderly	0.52

Migration Variables

Variable 1	Variable 2	Correlation
RefuPop	NMgr	0.24
RefuPop	remittances	0.50
RefuPop	MgrStock	0.39
RefuPop	MgrStock_pct	0.35
NMgr	remittances	0.75
NMgr	MgrStock	0.73
NMgr	MgrStock_pct	0.72
remittances	MgrStock	0.87
remittances	MgrStock_pct	0.85
MgrStock	MgrStock_pct	1.00

Labour Market Variables

Variable 1	Variable 2	Correlation
LFPR	EmpR	-0.38
LFPR	emp_agri	-0.95
LFPR	emp_ind	-0.92
LFPR	emp_serv	0.94
LFPR	gdp_pc_gr	-0.10

EmpR	emp_agri	0.54
EmpR	emp_ind	0.65
EmpR	emp_serv	-0.60
EmpR	gdp_pc_gr	0.07
emp_agri	emp_ind	0.98
emp_agri	emp_serv	-0.99
emp_agri	gdp_pc_gr	0.09
emp_ind	emp_serv	-1.00
emp_ind	gdp_pc_gr	0.09
emp_serv	gdp_pc_gr	-0.09

Appendix_4: Table 3.2.4: Summary of variables' deterministic properties (level, log-level, differenced log-level)

Variable	Level		Variable	Log-Level		Variable	Differenced Log-level		
	Lag-length	P- value		Lag-length	P- value		Lag-lengt	P- value	Conclusion
TPA_65+		0.99	L_TPA_65+		0.03	DL_TPA_65+		0.02	I (1)
OADR		0.99	L_OADR		0.07	DL_OADR		0.01	I (1)
LifExp		0.01	L_LifExp		0.09	DL_LifExp		0.03	I (1)
TFR		0.98	L_TFR		0.02	DL_TFR		0.05	I (1)
NMgr		0.31	L_NMgr		0.10	DL_NMgr		0.02	I (1)
LFPR		0.34	L_LFPR		0.20	DL_LFPR		0.01	I (1)
gdp_pc_gr		0.26	L_gdp_pc_gr		0.04	DL_gdp_pc_gr		0.00	I (1)
TPA_65+		0.99	L_TPA_65+		0.03	DL_TPA_65+		0.02	I (1)