

# **EUROPEAN DEMOGRAPHIC CHALLENGES: AGEING PATHWAYS AND MIGRATION PATTERNS**

## **ABSTRACT**

European countries are currently experiencing low to negative population growth rates, while the proportion of older adults living until a very old age is growing. The process is conventionally described through the paradigm of the demographic transition and linked to the slow pace and long-term predictability of population changes. However, ageing is not uniform across European regions, and differences become even more evident when looking at finer territorial units, where it has important implications, not only for economic development, but also for the social cohesion of populations. The paper aims to investigate the role played by demographic components in reshaping population size at local levels. Migratory movements have short-medium-term age-specific effects, contributing to potential shifts in demographic determinants of population changes. This fast demography perspective would feed future research to enhance our understanding of differences in population dynamics across European territories.

## **1. SLOW AND FAST DEMOGRAPHIC CHALLENGES IN CONTEXT OF LOW FERTILITY**

Europe is undergoing a profound demographic transformation, marked by persistently low, or even negative, population growth and a rapidly increasing proportion of older adults. Trends in fertility and mortality, on one side, and migration on the other side, are changing the size, composition, and distribution of the European population at two different paces (Billari 2022; Van Nimwegen 2013). Whereas changes in population size arising from fertility and mortality tend to reshape demographic structures slowly and progressively, migration, whether internal or international, can trigger sudden and pronounced shifts in local population dynamics (Friedlander 1969; Schoener and Spiller 1987; Stewman 1988; Ghio et al. 2024). Indeed, while such trends are often framed within the classic demographic transition paradigm, highlighting long-term, gradual demographic change (Roser 2023), a closer look reveals striking spatial disparities. These diverging trajectories impose unequal stress on welfare and health systems and demand a more nuanced demographic analysis at the local scale. The concept of fast demography foregrounds the idea that migration can produce swift shifts in population dynamics, especially in regions where ageing progresses rapidly (Billari 2022).

International migration has emerged as one of the most influential drivers of demographic change in Europe, with projections pointing to a potential increase by mid-century (Koser and Laczko 2010). Eurostat employs a set of *what-if* scenarios to illustrate how population trends in the European Union (EU) might evolve under different demographic assumptions (Eurostat 2023). Under the baseline scenario, the EU's population is projected to decline moderately, by around 6%, achieving approximately 419 million in 2100. However, under the no-migration scenario, the EU's population would shrink by more than one-third, reaching just 295 million. The age structure implications of the two scenarios also differ sharply: whereas in the baseline

scenario the share of people aged 65 and older is projected to range from 21% in 2024 to 32% by the end of the century, under the zero-migration assumption the proportion rises even further to 36%. In the absence of migration, EU member states would face not only more pronounced population size contraction but also a steeper increase in old-age dependency ratios, amplifying pressures on labour markets, welfare systems, and long-term care provision.

Several demographic and population structural factors can underpin the expansion of immigration waves, including population pressures in countries of origin, workforce decline and ageing in destination regions (Golini 2008). These factors interplay with environmental transformations, political, social and economic dynamics in complex and highly context-dependent ways (Black et al. 2011). International migrations and mobility patterns contribute to pronounced local heterogeneity, as their demographic and socio-economic impacts unfold unevenly across regions (Triandafyllidou et al. 2023). Recent studies have shown that while some European cities experience demographic shrinkage due to persistent population losses, others are revitalized by the inflow of younger migrants attracted by employment opportunities and urban amenities, producing diverse trajectories of urban and regional transformation. (Kabisch and Haase 2011; Kashnitsky *et al.* 2020; Ghio et al. 2022a).

At fine territorial scales, the interplay between cohort turnover (defined as the difference between the number of individuals entering the working-age cohorts and those exiting) and migration reveals complex patterns. Ghio et al. (2022b) estimate that only in a small subset of EU territories migration fully offset the demographic losses due to cohort turnover, with compensatory effect notably stronger in urban zones. Similarly, age-stratified migration patterns across municipalities show that young adults disproportionately relocate to urban areas, reinforcing urban demographic resilience and rural demographic challenges (Ghio et al. 2022a). Overall, marked spatial contrasts are evident (Van Nimwegen 2013): while certain regions face stagnation or even decline in their working-age populations, others continue to experience demographic expansion in this age group. Such regional asymmetries suggest that labour migration (whether intra-EU or from external origins) expands irregularly across EU, giving rise to differentiated national and regional demographic profiles and policy needs (Gesano et al. 2009). These insights call for a framework that understands migration as a dynamic, geographically patchy process whose distribution depends on local socio-economic contexts and might rapidly influence local population structure. Previous research has documented how a regional perspective provides a more refined understanding of demographic change and highlighted the spatial heterogeneity of migration flows, cohort turnover, and mortality, which often vary markedly across subnational regions (de Beer et al. 2011). This requires a regional-level approach to migration studies to capture differential impacts in labour force characteristics and demographic trajectories across territories and inform targeted policies.

In light of these considerations, the work aims to shed light on how migration has evolved at the EU regional level (NUTS-2), during the recent past decade (from 2012 to 2023) Specifically, the analysis investigates how and to what extent the interplay between socioeconomic conditions and migration would explain the evolution of EU regions. By applying Finite Mixtures of (linear) Gaussian Regressions (FMGR) model, the study uncovers clusters of European regions with shared socio-economic and migratory profiles, which experience homogeneous migration-economy linkages. Two model specifications are considered: one featuring only gross domestic product (GDP) per capita as the main economic factor influencing migration, and another including both GDP and unemployment rate. Results show a clear polarization of European

regions into *enduring attractors* and *persistent losers* of migrants, with extra-EU migration playing an increasingly central role in demographic dynamics.

The contribution is twofold. First, findings reveal how migration interacts with local socio-economic contexts to produce similarities and divergences in EU regional demographic trajectories. Second, this evidence supports the enhancing of EU regional policy by underling the needs for a better development of demographic resilience goals, as part of the EU cohesion programs, and the formulation of ad-hoc interventions to address the differentiated capacities of regions to attract and retain migrants.

The paper is structured as follows: Section 2 illustrates the slow and fast demographic paradigm; Section 3 outlines data sources and variables exploited in the analysis; Section 4 presents the methodological approach; Section 5 interprets results, emphasising the cluster configuration emerged from the models; Section 6 discusses findings and their relevance for a better understanding of EU regional challenges; and Section 7 presents the conclusive remarks and possible implications for policy making.

## **2. DEMOGRAPHIC HETEROGENEITIES ACROSS THE EU REGIONS**

Regional profiles are shaped by demographic dynamics operating at different speeds (Billari 2022).

The slow components, fertility and mortality, evolve gradually, generating long-term and relatively predictable transformations in population structures. Across the EU, fertility has remained persistently below replacement (2.1 children by woman). In 2023, the total fertility rate varies from 0.84 in Canarias (Spain) to 2.14 in Yugoiztochen (Bulgaria). Some other regions, like Ile de France and Bolzan in Italy, record relatively exceptional values of 1.71 and 1.57, respectively (Eurostat 2023). In parallel continuous improvements in mortality have produced sustained increases in life expectancy, leading to population ageing as larger cohorts survive into advanced ages (Chesnais 1990, Livi-Bacci 2017). For instance, according to the Eurostat database, regions such as Comunidad de Madrid in Spain and the Autonomous Province of Trento in Italy report the highest value in 2023 (86.1 and 85.1, respectively) while regions mainly located in the Eastern EU countries, such as Severozapaden and Eszak-Magyarorszag, report the lowest value (73.9 and 74.9, respectively). Some regions (such as Sardinia, and Ikaria) have been classified as blue zones, with the highest life expectancy in the world (Poulain et al. 2025). These components, which are inertial, cumulative, and largely impervious to short-term fluctuations, are mainly responsible for the structural population decline (deaths outnumbering births) which has characterised EU's demographic outlook throughout the twenty-first century (Eurostat 2023; United Nations 2024). Such slow-moving trends place a heavy and predictable burden on welfare systems, pensions, and health care, while gradually reshaping the balance between working-age and elderly populations (Bloom et al. 2003).

Against this backdrop, migration represents the fast demographic component, capable of producing sudden shifts in local population size and composition (Massey 1988). Unlike fertility and mortality, which change over decades, migration flows may alter demographic trajectories within a matter of years, but impacts at local level are neither guaranteed nor uniform (Ghio et al. 2022b). The spatial heterogeneity introduced by migration is therefore central in demographic

and social analyses. Whereas fertility and mortality tend to converge across regions due to shared structural determinants, migration is deeply contingent on local economic conditions, institutional frameworks, and historical pathways (Triandafyllidou and Maroukis 2012). Urban centres and economically dynamic regions typically attract younger, foreign-born populations who bolster workforce size and contribute to demographic rejuvenation, while rural and peripheral territories often remain unable to offset cohort losses, accentuating regional disparities in ageing and labour supply (Ghio et al. 2022b). This spatial unevenness reveals a dual role of migration: migration operates both as a mitigating factor against EU's demographic decline and as a mechanism that amplifies local demographic divergence (Bell et al. 2015; Rees et al. 2017).

Conceptualising migration within the fast demography paradigm clarifies its increasing relevance for European societies. Billari (2022) emphasises the growing role of migration in shaping demographic momentum: in regions with persistently low fertility, migration has become the main driver of population renewal. This dynamic applies for advanced economies with relatively large populations, where migration increasingly shapes demographic trajectories, but it is particularly relevant for small communities, where migration flows constitute the largest share of population turnover. Overall, the interplay between slow and fast components underscores that EU demographic future cannot be understood solely through the conventional lens of the demographic transition. While slow demography anchors long-term projections of population ageing (Coale 1968; Dyson 2010), fast demography illuminates the short- and medium-term contingencies that can either exacerbate or alleviate local challenges. Fertility and mortality trends ensure that natural decrease will persist across the continent, but the scale, distribution, and consequences of this decline will be potentially shaped by migration. As such, migration, intended both as international movements and internal mobility, is not merely an ancillary variable but a structural determinant of EU demographic trajectories capable of moderating natural decline, reshaping age structures, and producing deeply heterogeneous local outcomes.

### 3. DATA

The dataset analysed combines Eurostat subnational statistics on net migration rates in 2012 and 2023, and GDP per capita and unemployment rate in the age group 15-74 recorded in 2012 at the (NUTS-2) regional level for the EU-27 countries. Overseas territories and very small regions with fragmented data (e.g., French overseas *départements*) were excluded to ensure comparability. The final dataset comprises nearly the full set of EU regions, providing a broad coverage of the countries considered. In addition, auxiliary indicators such as life expectancy at birth and the percentage of individuals at risk of poverty and social exclusion, publicly available from Eurostat at NUTS-2 level, were used as post-estimators to characterise cluster profiles and interpret model results. This enriches the analysis by linking demographic outcomes with wider socio-economic and wellbeing dimensions.

In 2012, substantial regional disparities in economic performance and labour market conditions were evident across European regions. The distribution of GDP per capita ranged from a minimum of €3,632 in Severozapaden (Bulgaria) to a maximum of €87,628 in Luxembourg. The median value was €24,194, slightly below the mean of €24,674, indicating a right-skewed distribution driven by a few highly affluent regions. The interquartile range extended from €14,027 to €32,682, underscoring the wide socio-economic heterogeneity across European

regions. Labour market indicators displayed an equally marked variability. Regional unemployment rates spanned from 2.7% in Oberbayern, Tübingen, and Trier (all located in Germany) to 37.0% in Ceuta (Spain). The median unemployment rate stood at 8.9%, while the mean was higher, at 10.97%, again reflecting the influence of regions with exceptionally high unemployment. The interquartile range, between 6.25% and 14.55%, pointed to pronounced disparities in employment opportunities across the continent. The extent of regional inequalities in both economic output and labour market performance within the European Union emerged clearly at the onset of the 2010s.

Indeed, when comparing GDP per capita and unemployment levels across European macro-areas, a geographical divide becomes more evident. In 2012, Eastern Europe stood out as the least affluent part of the continent, with most regions recording GDP per capita levels well below the EU average. The median stopped at just under €9,000, and only a handful of regions exceeded €30,000. Labour market conditions were also fragile, with unemployment rates close to 10% on average and peaking at 19% in some areas, reflecting enduring structural imbalances. In the Mediterranean regions, economic output was higher than in the East, with median incomes close to €19,000, but this improvement was offset by severe labour market distress. The median unemployment rate reached almost 18% in the most disadvantaged regions, such as Ceuta. By contrast, the Scandinavian regions were among the most prosperous ones, with GDP per capita approaching €40,000 on median and exceeding €60,000 in the wealthiest regions. Crucially, unemployment remained contained, rarely surpassing 10%, which highlights the relative resilience of northern regional labour markets in the post-crisis period. Western-EU regions occupied an intermediate but favourable position: GDP levels were substantially above the EU average, with a median exceeding €30,000, and unemployment remained among the lowest in EU, generally between 4% and 8%. These figures highlight the existence of a twofold persistent North-Southern and East-Western regional divide: northern and western regions successfully combined high levels of prosperity with relatively low unemployment, whereas southern and eastern regions were marked by weaker economies and significantly higher labour market vulnerabilities.

#### **4. METHODS**

Two regression model specifications were tested to assess the influence of local socioeconomic conditions on the migration at regional level. The first model regressed net migration changes between 2012 and 2023 on GDP per capita (value recorded in 2012). This model definition stems from the classic theoretical literature (Friedman 1957; Borjas 1985), which reflects the assumption of economic prosperity as a driver of demographic attractiveness and identify income differentials as the main drivers of migration. The second model extended the analysis to the unemployment rate (value recorded in 2012), following the conceptualization formulated by the new-economics (Stark and Bloom 1985) that migration results from the disequilibrium between demand and supply of labour market. Specifically, the FMGR methodology was applied to identify the groups (or clusters) of regions where the regression predictors influence the change in net migration homogeneously, namely areas with similar and coherent dynamics. Therefore, the models' originality mainly consists in assessing whether economic (GDP) and labour market (unemployment rate) conditions influence migration over time and systematically generate regional clusters that transcend national borders. Doing so, FMGR provide a flexible approach

for capturing *latent* homogeneity / heterogeneity by assuming that populations under study are composed of unobserved subgroups, each governed by its own behavioural process.

Additionally, the (here developed) mixture regression models accounted for concomitant variables, such as the macro-regional dummy variable to categorize European regions by geographical characteristic. Generally, the use of concomitant variables would help predicting *latent* groups to whose members (individuals or statistical units, here the NUTS-2 areas) are more likely to belong. Rather than treating group membership randomly, these variables connect group assignment to observable characteristics, by combining the advantages of clustering with regression modelling techniques to capture the geographic structures (or geographies) of variation in the interplays between net-migration and economic conditions.

Additionally, the initial net migration rate (value recorded in 2012) is included as a concomitant predictor for the tracking of *path dependence*. The concept of *path dependence* is relevant in the population studies since it elaborates the idea of *mechanisms of influence*, meaning that current demographic trajectories are strongly influenced by initial conditions (Billari 2022). In this context, regions with high or low migration rates recorded in 2012 can exhibit the tendency to uphold these dynamics over time. The *perduring* aptitude would indicate that past migratory patterns are able to shape future migration flows, which may also be related to migrant social network effects (McKenzie 2017).

Formally, the models are given by:

$$H(y|x, w, \Theta) = \sum_{s=1}^S \pi_s(w, \alpha) N(y | \mu_s(x), \sigma_s^2) \quad (1)$$

where  $N(\cdot | \mu_s(x), \sigma_s^2)$  is the Gaussian distribution with mean  $\mu_s(x) = x' \beta^s$  and variance  $\sigma_s^2$ .  $\Theta$  denotes the vector of all parameters of the mixture distribution and the dependent variables are  $y$ , the independent  $x$  and the concomitant  $w$ .  $\pi_s(w, \alpha)$  are positive weights (depending on the parameters  $\alpha$ ) summing to one for each fixed  $w$ , while  $s=1, \dots, S$  are the mixture components, each one representing a latent subpopulation underlying the overall population (McLachlan and Basford 1988).

In general, the concomitant variable model is assumed to be a multinomial logit model, i.e. :

$$\pi_s(w, \alpha) = \frac{\exp(\alpha_{s0} + \alpha'_{s1} w)}{\sum_{u=1}^S \exp(\alpha_{u0} + \alpha'_{u1} w)} \quad \forall s \quad (2)$$

where  $\alpha_{s1} = (\alpha_{s1}, \dots, \alpha_{sd})'$ ,  $\alpha_s = (\alpha_{s0}, \alpha'_{s1} \mathbf{1}' \in \mathbb{R}^{d+1}$ , and  $\alpha = (\alpha'_1, \dots, \alpha'_s)$ , with  $\alpha_1 \equiv 0$  for identifiability sake (see Grün and Leisch 2008, p. 4). Using the mixture weights in equation (2), the concomitant variables  $w$  can effectively describe the profiles of the different groups or subpopulations. As explained above, it's crucial to underline that, according to the mixture model in equation (1), the models do not predefine the groups (or clusters). Instead, the observed characteristics of populations serve as means to identify homogeneous groups based on the relationship between  $y$  and  $x$ , namely the economic conditions and net-migration interplays.

More technical details on FMGR and its estimation are provided in Appendix A.

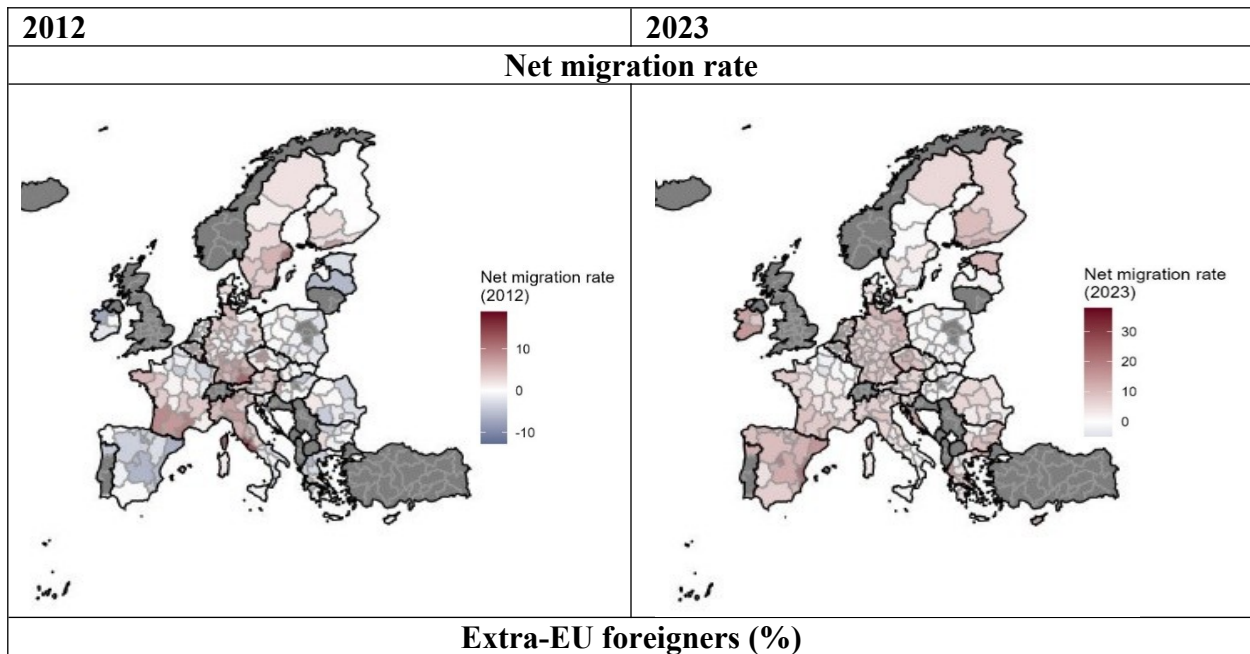
## 5. RESULTS

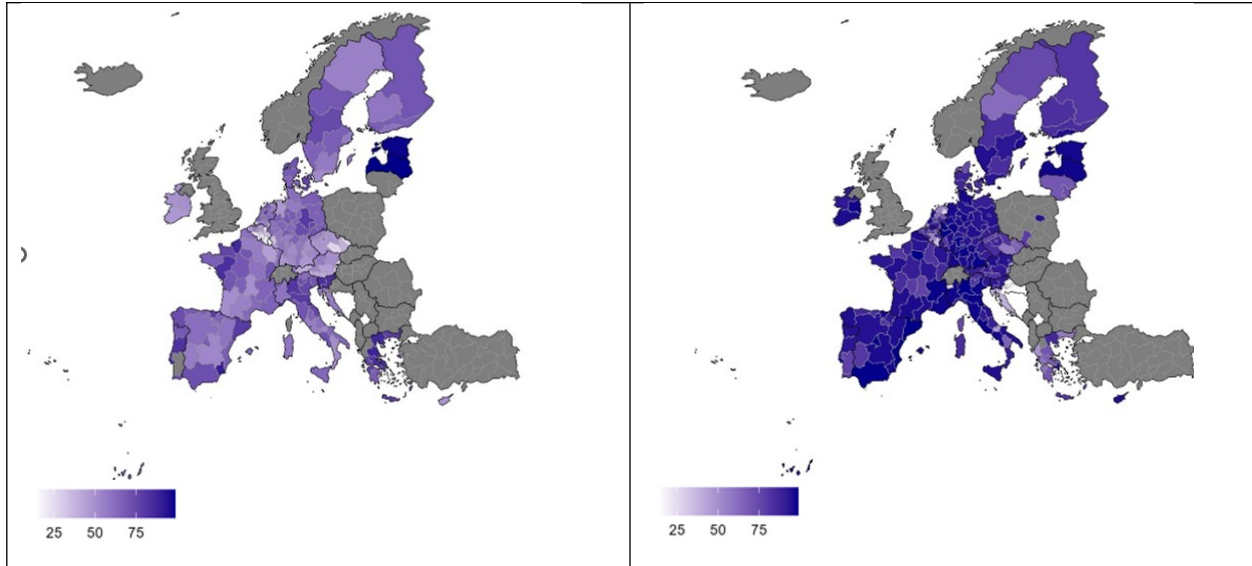
Overall, the comparative analysis of net migration and its geographical distribution reveals the shift from relatively localized patterns observed in 2012, with regions that gain and lose migrants, to a generally more positive and widely dispersed geography of net migration in 2023 (Figure 1). Precisely, in 2012, positive balances (in-flows higher than out-flows) are concentrated in the most economically dynamic regions, generally located in the central and Scandinavian areas. Many areas in Eastern Europe, as well as large parts of the Mediterranean, hovered around neutrality, with net migration close to zero since the compensation between inflows and outflows, whereas most regions in countries like Spain, Portugal, and Greece recorded clear losses (out-flows higher than in-flows).

By 2023, a much broader range of the areas, including several Central-Eastern and Southern regions, has experienced positive balances in net migration, while the areas where negative balances increase appear more scattered and confined to specific peripheral territories. These trends indicate a diffusion of migration gains and more polycentric spatial patterns when compared to the beginning period of analysis.

**Figure 1**

Net migration rates and extra-EU foreigners to total foreigners (%), 2012 and 2023, across European regions (NUTS-2).





Note: NA values and extra-EU27 regions in grey. Source: authors' elaboration on Eurostat data.

Since Eurostat data on net migration rates at regional level do not distinguish the origin of the migration flows, the contribution of EU immigrants and extra-EU immigrants cannot be disentangled. Nevertheless, the shares of extra-EU (the proportion of extra-EU population on the total population living in the region) and the share of EU immigrants (the proportion of EU population on the total population living in the region) at the beginning and the end of the period (Figure 1) offers a useful perspective for drawing some important insights. During the observed period, the balance between the shares of extra-EU and intra-EU immigrants has changed significantly across European regions, pointing to a structural transformation in migration patterns. In 2012, the prevalence of EU citizens among immigrants is comparatively higher than the proportion of extra-EU immigrants, with several regions in Northern and Eastern Europe displaying strong concentrations of EU immigrants as a result of intense intra-EU mobility.

Over the following decade, however, the relative weight of extra-EU immigrants increased markedly, leading to more homogeneous spatial patterns. By 2023, a growing number of regions in Southern and Western Europe record proportions of extra-EU residents that not only rival but, in many cases, surpassed those of EU ones. This change is indicative of both the sustained diversification of migratory inflows and the rising importance of international migration channels in shaping European demographic structures. Although intra-EU mobility remains an essential component of regional population turnover, its relatively declined importance underscores the increasing demographic role of extra-EU migration, particularly in areas characterized by stronger labour market demand.

## 6. THE INTERPLAY BETWEEN ECONOMIC CONDITIONS AND MIGRATION

Both the mixture models' configurations yield coherent results and identify the same clusters of regions. While the substantive regional geography of migration (winners and losers) remains unchanged when excluding or including unemployment variables, the second model results give

a more refined distinction of clusters. This means that unemployment rate strengthens the separation between declining and resilient regions, which is consistent with neoclassical conceptualizations. For the sake of brevity, the discussion in the following paragraphs is limited to the results of the second model.

The four clusters of regions selected by the model are displayed in Figure 2. They represent four *latent* regimes of migration-driven population change, that can be described as follows.

*Cluster 1*, labelled as *structurally disadvantaged areas*, which comprises regions with the lowest levels of economic development (GDP around €16,000), the highest unemployment rates (close to 15%), elevated poverty ( $\approx 27.6\%$ ), and the shortest life expectancy ( $\approx 79.8$  years). Predominantly located in Eastern and Mediterranean Europe, these territories exhibit a negative migration balance in 2012 and persistent patterns of out-migration during the interval 2012-2023. The regional migration profile of Cluster 1 reflects how structural socio-economic disadvantages reinforce cumulative demographic decline. For instance, Italian southern regions (such as Calabria and Sicily) and Bulgarian regions (such as Yugozapaden and Severoiztochen) are part of this group.

*Cluster 2*, labelled as *persistent attractors*, represents the opposite end of the spectrum proposed by Cluster 1. Indeed, *Cluster 2* encompasses the wealthiest and most demographically advantaged regions, with GDP exceeding €33,000, very low unemployment ( $\approx 7.8\%$ ), the lowest poverty incidence ( $\approx 19.4\%$ ), and the highest life expectancy ( $\approx 81.9$  years). Concentrated in Western and Scandinavian Europe, these areas display stable to moderately positive net migration dynamics, although their initial (2012) migration surplus was substantially higher than the value reported in 2023. This attenuation signals the relative advantage in attracting migrants of these regions has diminished over the past decade. For example, the regions of Lombardy and Veneto in the North of Italy and Oberbayern and Stuttgart in Southern Germany.

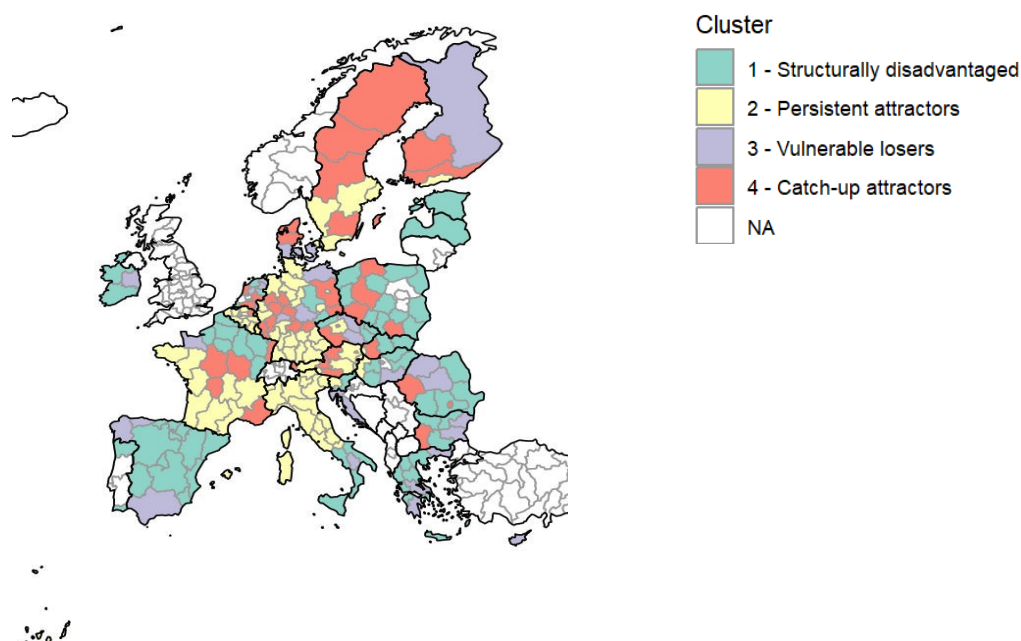
*Cluster 3*, labelled as *vulnerable losers*, presents a distinct group of regions with a specific migration trajectory, which confirms the neo-classical paradigm attesting how entrenched socio-economic vulnerabilities of the regional labour markets can rapidly translate into substantial out-migration. Although GDP levels ( $\sim \text{€}20,700$ ) are somewhat higher than those of structurally disadvantaged regions (Cluster 1), the combination of high unemployment ( $\approx 13.8\%$ ) and persistent poverty ( $\approx 26.3\%$ ) erodes population sustainability. With an average life expectancy of around 80 years, these territories, largely concentrated in the Mediterranean and parts of Eastern Europe, exhibited stable migration balances at the beginning of the period but have shifted into severe decline during the observed period. This is typically the case of Galicia in the Northwestern part of Spain and Nord-Vest in Romania.

*Cluster 4*, labelled as *catch-up attractors*, includes regions with relatively high GDP ( $\sim \text{€}28,600$ ), the lowest unemployment across all groups ( $\approx 6.6\%$ ), the lowest poverty incidence ( $\approx 18.0\%$ ), and a life expectancy comparable to that of core winners ( $\sim 80.7$ ). Mainly located in Western Europe, these regions maintain a consistently positive migratory balance ( $\approx +2.2$ ), building upon a slightly positive migration balance in 2012. Their regional profile highlights the capacity of mid-high performing regions to combine favourable socio-economic conditions with sustained demographic gains, making them a second pole of attraction alongside the core winners of Cluster 1. For instance, these patterns are evident for the regions of Provence-Alpes-Côte d'Azur in the South of France, and Norra Mellansverige in central Sweden.

The cluster typology resulting from the analysis reveals a clear polarization of European regions into persistent *losers* and enduring *attractors*, with socio-economic disadvantage closely aligned with demographic decline, and robust labour markets and higher living standards underpinning migration-led growth. The list of regions belonging to each cluster is given in Appendix B.

**Figure 2**

Regional clusters of EU.



Cluster	Main characteristics (mean values)	Net migration (NM) dynamics	Interpretation
1 Structurally disadvantaged	Lowest GDP (16,214.29) highest unemployment (14.91) highest poverty (27.6) lowest life expectancy (79.8) Concentrated in Eastern and Mediterranean Europe	Persistent decline ( $\Delta NM = -2.48$ ) Initial moderate negative rate $NM = -0.28$ )	Disadvantaged socio-economic conditions drive continued out-migration
2 Persistent attractors	Highest GDP (33399.23) low unemployment (7.78) low poverty (19.4) highest life expectancy (81.9) Strongly represented in Western and Scandinavian Europe	Stable to positive trend ( $\Delta NM = 0.32$ ) Initial strongly positive rate ( $NM = 0.62$ )	Wealthiest, healthiest regions with persistent (but decreasing) migration attractiveness
3 Vulnerable losers	Low GDP (20725.46) high unemployment (13.84) high poverty (26.3) life expectancy (80.0) Over-represented in Mediterranean and Eastern Europe	Strong negative trend ( $\Delta NM = -10.30$ ) Initial stable rate ( $NM = -0.00$ )	” Weaker labor markets and persistent socio-economic disadvantages correspond to severe out-migration
4 Catch-up	Relatively high GDP (28615.56) lowest unemployment (6.64)	Positive trend ( $\Delta NM = 2.25$ )	Favourable socio-economic profile sustains

attractors	lowest poverty (18.0) life expectancy (80.7) Mostly Western Europe	Initial slight positive rate (NM=1.78)	the highest migration gains
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Note:  $\Delta$ NM= change in net migration rates between 2012 and 2023

### *Results' robustness and sensitivity*

The mixture regression model identifies a four-cluster structure that includes markedly different socio-economic and demographic regimes across European regions. By competing solutions with different number of clusters ( $K=1, \dots, 10$ ), the analysis confirms  $K=4$  as the cluster number composition that optimizes the trade-off between the model fit and its complexity (the Bayesian Information Criterion (BIC) is minimized and yielded interpretable, with stable clusters across starts). Moran's I indicator checks on component-specific residuals attests no strong spatial autocorrelation given the index's values ranging around zero for all the clusters (Appendix C).

## 7. DISCUSSION

The mixture regression results (Table 1) reveal substantial heterogeneity in the direction, magnitude, and statistical significance of the interplays between net migration and socio-economic conditions across clusters.

**Table 1**

Parameter estimates

Cluster	Cluster size	Covariates	Estimate	Std. Error	t value	p value	
1 Structurally disadvantaged	0.32	(Intercept)	-2.985	0.442	-6.755	0.000	***
		GDP (2012)	-0.949	0.422	-2.248	0.028	*
		Unemployment (2012)	-0.133	0.312	-0.427	0.671	
2 Persistent attractors	0.35	(Intercept)	0.367	0.092	3.976	0.000	***
		GDP (2012)	-0.168	0.080	-2.101	0.039	*
		Unemployment (2012)	-0.121	0.101	-1.198	0.235	
3 Vulnerable losers	0.14	(Intercept)	-6.905	7.566	-0.913	0.369	
		GDP (2012)	4.554	8.209	0.555	0.583	
		Unemployment (2012)	-3.798	6.099	-0.623	0.538	
4 Catch-up attractors	0.19	(Intercept)	0.409	0.516	0.793	0.433	
		GDP (2012)	-0.757	0.324	-2.334	0.025	*
		Unemployment (2012)	-3.299	0.770	-4.284	0.000	***

The GDP per capita in 2012 enters with a negative coefficient in three of the four *clusters* (1, 2, and 4). This may appear counterintuitive and contrasting with the specificities of regional profiles by cluster; nevertheless, it can be explained by path dependence, namely the persistence of initial conditions, which implies that regions with higher GDP per capita in 2012 generally experienced comparatively slower growth than those with lower initial levels. These results are in line with the evidence of *convergence* in the economic sphere identified by Borsi and Metiu (2015), who argue that European economies do not converge uniformly but instead coalesce into *clubs*, geographically determined groups. At the same time, compared with the European convergence machine, more optimistically advanced by Bisciari and colleagues (2020), but still functioning albeit interrupted by crises, the present demographic perspective underscores the fragility of convergence, since migration simultaneously alleviates population decline at the continental level and deepens divergence at the regional scale. As a consequence, income differentials across Europe narrowed by 2022, reducing relative differences in migratory attractiveness. It should also be emphasised that 2012-2023 net migration differential captures relative dynamics, quantifying regional gains or losses relative to initial values. For instance, when a region records both high GDP and high net migration in 2012, it can be largely expected that 2012-2023 changes in net migration would be close to zero. Thus, a negative coefficient does not imply that wealthier regions *repel* migrants, but rather that the positive link between economic (income and labour market) prosperity and migration attractiveness interplays is not linear (neither infinite). Beyond a certain level of interactions between economic conditions and migration, other factors (such as labour market saturation, cost of living, urban congestion) can also reduce the relative advantage of *richer* regions, such as for the provinces of Hainaut and Namur, in Belgium or for Pays de la Loire and Bretagne, in the Northwestern areas of France.

Within the structurally *disadvantaged regions* (*Cluster 1*), territories with relatively higher GDP in 2012 experience a sharper decline in net migration over the 2012-2023 interval. This negative trend may reflect both greater propensity of populations to emigrate from slightly better-off areas, where infrastructural resources and individual networks can facilitate mobility, and the fact that modestly higher income levels are not systematically associated with improved labour market opportunities; GDP thus fails to act as a protective factor. In such disadvantaged contexts, GDP can even be associated with stronger out-migration.

To assure joint, comparability of economic variables and net migration effects across regions, predictors' coefficients have been standardized (z-scores). As reported in Appendix D, effects are statistically significant. These results show that higher initial economic levels which are associated with subsequent relative declines in migration performance, can be interpreted as a sort of saturation effects irradiated to more affluent regions. For instance, this is the case of the northern provinces of Italy. By contrast, for regions belonging to *Cluster 3* (*vulnerable losers*), where GDP per capita is positive and coefficients are non-significant, there are other factors influencing the migration evolution.

Unemployment effects, in turn, demonstrate far greater variability than GDP ones across EU regions. In *Cluster 1-2-3*, the coefficient is negative but non-significant, indicating that labour market conditions are not systematically able to differentiate migration outcomes at regional levels. Only for regions belonging to *Cluster 4* (*catch-up attractors*), unemployment rate emerges as a decisive factor, with a large and highly significant negative coefficient. This highlights that, for this subset of regions, high unemployment substantially undermines migration performance, even after controlling for GDP. This is the case of Centre-Val-de-Loire

and Bourgogne, in Central France or Etelä-Suomi and Länsi-Suomi, in the southern part of Finland.

## 8. CONCLUSIVE REMARKS

Findings reveal that cross-national differences matter less than country socio-economic profiles: clusters cut across national borders, grouping together regions with similar structural endowments and labour market characteristics. Migration dynamics between 2012 and 2023 are therefore adequately explained by intra-European disparities in prosperity and employment opportunities. Moreover, the persistent significance of initial net migration conditions indicates that demographic trajectories are strongly path-dependent, reinforcing the importance of baseline dynamics.

Migration is not merely a static buffer compensating for demographic imbalances, but a dynamic and territorially uneven process that reshapes regional population structures in Europe. Between 2012 and 2023, net migration patterns shifted from a geography of localized gains to a more polycentric configuration, while the relative weight of extra-EU migrants increased markedly, underscoring the global dimension of Europe's demographic future. The here proposed mixture regression identified four *latent* clusters, revealing a strong polarization: *persistent attractors* in Western and Northern Europe, *structurally disadvantaged* and *vulnerable losers* in Eastern and Mediterranean regions, and a set of *catch-up attractors* that combined relatively favourable socio-economic conditions with sustained demographic gains. Importantly, the negative coefficients for initial GDP highlight saturation effects and relative convergence: wealthier regions remain attractive but no longer increase their lead, whereas mid-income regions gain ground. Only in a subset of resilient regions unemployment emerges as a decisive factor undermining migration performance.

From a methodological point of view, the analysis contributes to the literature showing how mixture modelling represents an essential tool to disentangle not only the highly-context dependency of migration drivers, but also that the heterogeneous interactions of migration factors and related dynamics over time across territories.

From a policy perspective, the analysis stresses the importance of path dependence in demographic trajectories, while also showing that socio-economic disadvantage aligns closely with demographic decline. This gives empirical evidence of regional diversity and underscores the need for EU Cohesion Policy to complement demographic dynamics more explicitly. Evidence from recent evaluations shows that Cohesion Policy has exerted a positive impact on growth and employment at the EU level, but with highly uncertain territorial outcomes: much of the growth bonus (intended as the additional regional economic growth attributable to EU Cohesion Policy investments) is concentrated in Germany, while Southern European beneficiaries display weaker or short-lived gains (Crescenzi and Giua 2020). These differences point to the decisive role of national institutional capacity and policy models in mediating the translation of EU fund-transfers into local development. Within this context, the experience of *catch-up attractors* is particularly instructive: mid-performing regions with relatively low

unemployment but moderate GDP levels have been able to leverage both migration inflows and EU policy support to improve their demographic outlook. Their trajectory indicates that, when funds are coupled with functioning labour markets and adequate infrastructures, EU support can help transform latent potential into durable attractiveness. In this perspective, our results contribute to the policy debate by highlighting that the demographic impact of migration cannot be disentangled from the economic and institutional environment. Future policy design should therefore pursue a dual strategy: i) strengthen the alignment between Cohesion Policy priorities, labour-market integration of migrants, and place-based social infrastructures; and ii) enhance administrative quality to ensure that funds effectively translate into job creation and improved living conditions. By doing so, EU regional policy can mitigate demographic divergence and transform fast demographic shifts into an asset for long-term cohesion and competitiveness.

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## APPENDIX A

Given a random sample  $(y_1, x_1', w_1')', \dots, (y_n, x_n', w_n')'$  of  $(Y, X, W)$  from model (1), and once  $s$  is assigned, the algorithm considers the complete-data log-likelihood

$$l_c(\Theta) = \sum_{i=1}^n \sum_{s=1}^S z_{is} \ln[\pi_s(w_i, \alpha)] + \sum_{i=1}^n \sum_{s=1}^S z_{is} \ln[p(y_i \vee x_i; \beta_s, \sigma_j)] \quad (1.A)$$

Here,  $z_{is} = 1$  if  $(y_i, x_i', w_i')$  comes from component  $s$  and  $z_{is} = 0$  otherwise. The EM algorithm alternates between two steps, an E-step and an M-step, until it converges. Their details, with respect to model (1), are provided below (Wedel and DeSarbo 1995; Wedel and Kamakura 2000, pp. 120–124).

E-step:

Given the current parameter estimates  $\Theta^{(r)}$  of the  $r$ -th iteration, each  $z_{is}$  is replaced by the estimated posterior probability.

$$z_{is}^{(r)} = \pi_s(w_i; \alpha^{(r)}) \phi \quad (2.A)$$

M-step:

The obtained values  $z_{is}^{(r)}$ , which are functions of  $\Theta^{(r)}$ , are substituted for  $z_{is}$  in (1.A), leading to the expected complete-data log-likelihood, which is maximized with respect to  $\Theta$ , subject to constraints on these parameters. Note that, since the two terms on the right-hand side of (1.A) have zero cross-derivatives, they can be maximized separately. The EM algorithm requires initialization. Among various initialization strategies (see Bagnato and Punzo 2013; Biernacki et al. 2003 and Karlis and Xekalaki 2003 for details), in the real data analysis, a random initialization is repeated 10 times from different starting positions (achieved using the argument `nrep=10` in the `stepFlexmix()` function), and the solution that maximizes the observed-data log-likelihood among these 10 runs is selected. Once the model is fitted, the posterior probabilities of group membership can be estimated, denoted  $\hat{z}_{is}$ , based on (2.A). Therefore, each NUTS 2 region can be assigned to one of the  $s$  groups using the maximum a posteriori probability operator  $\text{MAP}(\hat{z}_{is})$ , which takes the value 1 if  $\max_{s=1, \dots, S} \{\hat{z}_{is}\}$  occurs at component  $s$  and 0 otherwise.

A common approach to selecting the number of components involves computing a suitable (likelihood-based) model selection criterion over a plausible range of  $s$  values and then choosing the value of  $s$  that optimizes the selected criterion. For the present application, the Bayesian information criterion (Schwarz 1978) is used, defined as:

$$BIC = -2l(\hat{\Theta}) + m \ln n \quad (3.A)$$

where  $m$  is the total number of free parameters in the model and  $l(\hat{\Theta})$  represents the maximized observed-data log-likelihood.

The analysis relies on the *flexmix* package in R, which implements expectation-maximisation algorithms for estimating FMGR with concomitant variables. To find maximum likelihood (ML) estimates for  $\Theta$  in (1), the EM algorithm was performed following Dempster *et al.* (1977) and

Richardson and Green (1997) as implemented by the `stepFlexmix()` function of the *flexmix* package (Grün and Leisch 2008; Leisch 2004) for the R environment (R Core Team 2025).

## APPENDIX B

### Cluster composition

- Cluster 1: Eastern Europe:** Dél-Dunántúl, Eesti, Kujawsko-Pomorskie, Közép-Dunántúl, Latvija, Lubelskie, Lubuskie, Łódzkie, Moravskoslezsko, Nord-Est, Opolskie, Podkarpackie, Podlaskie, Severen tsentralen, Severozapaden, Severozápad, Slaskie, Stredné Slovensko, Strední Morava, Sud - Muntenia, Sud-Est, Sud-Vest Oltenia, Swietokrzyskie, Východné Slovensko, Warminsko-Mazurskie, Yuzhen tsentralen, Zachodniopomorskie, Észak-Alföld, Észak-Magyarország; **Mediterranean Europe:** Algarve, Aragón, Attiki, Calabria, Campania, Cantabria, Castilla y León, Castilla-la Mancha, Cataluña, Comunidad Foral de Navarra, Comunidad Valenciana, Comunidad de Madrid, Dytiki Ellada, Dytiki Makedonia, Extremadura, Ionia Nisia, Ipeiros, Kentriki Makedonia, Kriti, La Rioja, Norte, Notio Aigaio, País Vasco, Puglia, Região Autónoma da Madeira (PT), Región de Murcia, Sicilia, Thessalia, Vzhodna Slovenija; **Western-continental Europe:** Champagne-Ardenne, Chemnitz, Drenthe, Franche-Comté, Friesland (NL), Haute-Normandie, Lorraine, Nord-Pas de Calais, Northern and Western, Overijssel, Picardie, Sachsen-Anhalt, Southern, Zeeland, Île de France.
- Cluster 2: Eastern Europe:** Bratislavský kraj, Nyugat-Dunántúl, Strední Čechy; **Mediterranean Europe:** Abruzzo, Canarias (ES), Ciudad Autónoma de Melilla (ES), Emilia-Romagna, Friuli-Venezia Giulia, Illes Balears, Lazio, Liguria, Lombardia, Malta, Marche, Molise, Piemonte, Provincia Autonoma di Bolzano/Bozen, Provincia Autonoma di Trento, Sardegna, Toscana, Umbria, Valle d'Aosta/Vallée d'Aoste, Veneto, Zahodna Slovenija; **Scandinavian Europe:** Helsinki-Uusimaa, Hovedstaden, Stockholm, Sydsverige, Västsverige, Östra Mellansverige; **Western-continental Europe:** Aquitaine, Auvergne, Berlin, Bremen, Bretagne, Burgenland (AT), Corse, Darmstadt, Düsseldorf, Freiburg, Hamburg, Hannover, Karlsruhe, Köln, Languedoc-Roussillon, Leipzig, Luxembourg, Lüneburg, Midi-Pyrénées, Mittelfranken, Niederbayern, Niederösterreich, Oberbayern, Oberpfalz, Pays de la Loire, Poitou-Charentes, Prov. Antwerpen, Prov. Brabant Wallon, Prov. Hainaut, Prov. Liège, Prov. Luxembourg (BE), Prov. Namur, Prov. Vlaams-Brabant, nProv. West-Vlaanderen, Rheinessen-Pfalz, Rhône-Alpes, Région de Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest, Schleswig-Holstein, Schwaben, Steiermark, Stuttgart, Tirol, Tübingen, Weser-Ems, Wien.
- Cluster 3: Eastern Europe:** Centru, Dolnoslaskie, Dél-Alföld, Jihovýchod, Nord-Vest, Severoiztochen, Severovýchod, Wielkopolskie, Yugoiztochen; **Mediterranean Europe:** Anatoliki Makedonia, Thraki, Andalucía, Basilicata, Galicia, Jadranska Hrvatska, Kypros, Principado de Asturias, Região Autónoma dos Açores (PT), Voreio Aigaio; **Scandinavian Europe:** Pohjois- ja Itä-Suomi, Sjælland, Syddanmark; **Western-continental Europe:** Basse-Normandie, Eastern and Midland, Flevoland, Gießen, Limburg (NL), Mecklenburg-Vorpommern, Thüringen.

4. **Cluster 4: Eastern Europe:** Bucuresti - Ilfov, Jihozápad, Malopolskie, Pomorskie, Praha, Vest, Jugozapaden, Západné Slovensko; **Mediterranean Europe:** Ciudad Autónoma de Ceuta (ES), Peloponnisos, Sterea Ellada; **Scandinavian Europe:** Etelä-Suomi, Länsi-Suomi, Mellersta Norrland, Midtjylland, Nordjylland, Norra Mellansverige, Småland med öarna, Övre Norrland; **Western-continental Europe:** Alsace, Arnsberg, Bourgogne, Brandenburg, Braunschweig, Centre - Val de Loire, Detmold, Dresden, Gelderland, Groningen, Kassel, Koblenz, Kärnten, Limousin, Münster, Noord-Brabant, Noord-Holland, Oberfranken, Oberösterreich, Prov. Limburg (BE), Prov. Oost-Vlaanderen, Provence-Alpes-Côte d'Azur, Saarland, Salzburg, Trier, Unterfranken, Vorarlberg.

## APPENDIX C

Moran's I test for spatial autocorrelation detection across cluster-specific residuals.

Cluster	Morans' I	p-value
1 Structurally disadvantaged	0.017	0.317
2 Persistent attractors	0.057	0.096
3 Vulnerable losers	0.024	0.272
4 Catch-up attractors	0.041	0.163