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Regional Dynamics of Innovation in Europe 2000-2020

A Tale of Convergence, Persistence, and the Illusion of Catch-Up

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Abstract

This study examines the dynamics of regional innovation activity in Europe from 2000 to 2020 using patent applications. Standard convergence measures indicate that regional disparities are narrowing, with initially lagging regions catching up to the leading ones. Our analysis reveals two persistent ‘clubs’: the ‘lagging’ and the ‘advanced’ regions. Although these groups are becoming increasingly similar, the differences between them remain largely unchanged. Despite two decades of growth, the disparity between the two clubs still accounts for a great deal of the total variation in regional patenting. These patterns suggest a convergence illusion that is overlooked in the current scholarly debate.

Keywords: regional innovation, convergence, convergence clubs, European regions

JEL codes: O31, R11, O47

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1. Introduction¹

Innovation plays a crucial role in driving regional development; however, its distribution across European regions remains highly uneven. This unevenness can lead to populism and social unrest (Rodríguez-Pose, 2018), which, in turn, can negatively impact innovation activities (Tang et al., 2024; Rodríguez-Pose et al., 2025). Despite various policy initiatives aimed at promoting innovation in Europe, particularly in less-developed regions, significant regional disparities still exist.

According to catching-up theories, ‘lagging’ regions are expected to experience higher rates of innovation due to knowledge diffusion and technology spillovers from more ‘advanced’ areas (Barro & Sala-i-Martin, 1992; Jaffe et al., 1993). However, structural factors such as differences in industrial specialization, institutional quality, and limited access to highly trained personnel can impede this convergence (see, e.g., Capello & Lenzi, 2015).

Understanding the dynamics of regional innovation activities and assessing how lagging regions are catching up is crucial for shaping policies that promote economic cohesion and long-term growth within the European Union. To achieve this, for example, the EU has made innovation policies a central element of its regional economic integration strategy. This strategy aims to create a unified European Research Area that fosters knowledge exchange and technological progress (Crescenzi & Rodríguez-Pose, 2011).

This paper examines the long-term evolution of regional innovation activity in Europe from 2000 to 2020, focusing specifically on patterns of convergence. Using patent applications from the OECD RegPat database as a proxy for innovation, we analyze regional trends at the NUTS-2 level across EU member states, Norway, Switzerland, and the UK.²

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² Our analysis does not include years prior to 2000 because during that time, post-socialist regions were still significantly influenced by the transition from state-controlled to market-based innovation.

Our findings reveal a paradox. According to standard convergence metrics, such as beta convergence, sigma convergence, and compound annual growth rates, lagging regions appear to be catching up. However, we observe a persistent two-club structure that has remained largely unchanged over the past two decades: an advanced core and a lagging periphery, with a mean patent intensity ratio exceeding 12:1. The variance decomposition analysis shows that the between-club component still accounts for over 67% of total inequality, despite two decades of aggregate convergence. Furthermore, the transition matrix indicates near-perfect persistence, with approximately 94% of regions remaining in their original club. We term this phenomenon the ‘convergence illusion.’ While standard metrics suggest a catch-up, the structural divide between the two groups remains fundamentally stable. This indicates that the convergence observed in aggregate statistics primarily reflects homogenization within each club, in which lagging regions become more similar to one another rather than advancing towards the level of the advanced club.

Our finding resonates with the literature, which reports similar patterns for income and GDP.³ We extend the analysis by Barrios et al. (2019) on innovation convergence patterns by providing a longer-term perspective (2000-2020 rather than 2002-2012), capturing post-socialist transition effects and recent trends such as EU integration and digitalization. Furthermore, we contribute to the convergence literature by demonstrating, over a longer period, that aggregate convergence masks intra-club homogenization (lagging regions become more similar to one another, not to advanced regions). Finally, our work additionally links to the debate on historical legacies to explain differences across lagging regions in Eastern and Southern Europe (e.g., Capello & Lenzi, 2017; Radošević, 2002, 2022; Fritsch et al., 2025).

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature. In Section 3, we describe the data and document the long-term development of innovation activities in European regions. Section 4 analyzes overall

systems. The analysis concludes in 2020, as records from the European Patent Office typically take three to four years to become reasonably complete after filing.

³ For relevant literature, see works by Quah (1996, 1997), Phillips and Sul (2007), Bartkowska & Riedl (2012), Cutrini (2019), Postiglione et al. (2017), and Cutrini & Mendez (2023).

convergence. An in-depth examination of regional structures in Section 5 identifies two convergence clubs and the long-term transitions between these groups. Finally, Section 6 discusses the implications for policy, theory development, and future research.

2. Theory framework

2.1 The case for convergence of innovation activity

Innovation serves as a primary driver of long-term productivity, competitiveness, and economic growth (e.g., Schumpeter, 1934; Aghion & Howitt, 1992; Crescenzi & Rodríguez-Pose, 2011). As a result, innovation activity has become a key focus for policies aimed at stimulating growth (European Commission, 2025).

The debate over whether regional innovation activity is converging or diverging is a well-established topic in economic geography and innovation research. Neoclassical growth theory posits that convergence should occur because market forces, particularly the geographic mobility of goods and resources, enable less innovative regions to catch up with their more advanced counterparts (Sala-i-Martin, 1996).

Conversely, alternative perspectives, such as those based on the principle of cumulative causation, argue for a ‘vicious circle’ in which highly innovative regions continue to outpace lagging ones, resulting in persistent and even growing disparities (e.g., Kaldor, 1970; Myrdal, 1957). New growth theory (Romer, 1986; Martin & Sunley, 1998) suggests that convergence in regional innovation output depends on the intensity of knowledge flows from advanced regions to lagging regions, as well as the latter’s absorptive capacity. Key factors influencing the extent of spillover effects include collaborative R&D activities, the skills and absorptive capacity of the regional workforce, and the mobility of innovative agents across regions and organizations.

Theories of regional development (see, e.g., Krugman, 1991; Glaeser, 2011; Carlino & Kerr, 2015; Florida et al., 2017; for a survey of the stylized facts, Feldman

& Kogler, 2010) suggest that agglomerated regions, such as large cities or industrial hubs, have significant advantages in innovation activities due to their abundant local knowledge, dense labor markets, and supportive infrastructure. However, recent evidence (e.g., Fritsch & Wyrwich, 2021) indicates that these advantages may not be as substantial as previously thought, as many peripheral and rural regions can also innovate successfully. This suggests that lagging regions have the potential to catch up in innovation activity, leading to long-term convergence in economic welfare.

Nonetheless, it remains unclear whether a general trend of convergent R&D activity exists across regions, what the timeframe for convergence might be, and how policy could facilitate these processes (Iammarino, Rodríguez-Pose & Storper, 2019).⁴ The degree of convergence may depend on a geographic area's level of development. Moreover, innovation convergence may be closely associated with structural economic shifts and path dependence, such as historical legacies and institutional lock-ins, which can trap some regions in stable, low-innovation equilibria, as seen in parts of post-socialist Eastern Europe (Radosevic, 2002; Fritsch et al., 2025).

It is also possible that there are distinct steady states with respect to innovation, much like for income. Empirical studies on the geographic patterns of income often identify various groups of countries and regions, highlighting multiple patterns of convergence toward distinct steady states rather than a single one (Quah, 1996, 1997). This means that poorer countries or regions do not necessarily catch up to wealthier ones; instead, they may converge toward a lower-income steady state. On the contrary, wealthier countries tend to converge to a higher level of welfare. This suggests the existence of 'convergence clubs' in which groups of countries with similar initial conditions, such as institutions, technology or human capital, tend to converge toward their respective steady states.

⁴ Key policy questions include whether support should be directed toward innovation systems in lagging regions (e.g., through R&D subsidies or the establishment of universities) to enhance innovation, or whether measures should focus on improving connectivity (e.g., transport, digital infrastructure, and inter-regional collaboration) to enable lagging regions to access external knowledge networks.

The concept of convergence clubs has shifted the focus from absolute convergence to conditional convergence, emphasizing that structural differences can lead to persistent disparities. The convergence-club framework was further refined and expanded by Phillips and Sul (2007). They were able to detect multiple steady states and classified regions into distinct clubs based on their transition paths. This approach was especially influential, as it provided a data-driven method for identifying these clubs and uncovering hidden patterns in economic and innovation data. Using the convergence-club framework, Bartkowska and Riedl (2012) identified distinct groups of European regions, each converging toward different long-term income levels. They demonstrated that a region's starting conditions, such as initial human capital and income per capita, play a critical role in determining which convergence club it joins, even after accounting for other structural factors.

For a better understanding of the convergence of innovation activities in Europe, it is important to examine regional differences in the conditions for and structure of innovation. We do this in the following section. Our focus is on historical legacies and institutional frameworks that vary substantially across space.

2.2 The evidence on regional differences in innovation activity in Europe

Several key developments shape the regional structure of innovation activity in Europe. One significant event was the collapse of socialism in many Central and Eastern European countries around 1990, followed by a transition to market economies that required a fundamental reorganization of their innovation systems (Radosevic, 2002). This transformation aimed to enhance the productivity of the innovation system and close the innovation gap with the established market economies of the West. However, the lingering effects of the socialist legacy on innovation, coupled with the turbulence of the transition process, may have hindered this progress. This raises the question of whether post-socialist regions have successfully caught up with the rest of Europe. Fritsch et al. (2025) demonstrate that in Germany, innovation between East and West diverged rather than converged after reunification, suggesting that the effects of the socialist legacy may still significantly shape innovation disparities.

Another aspect of the geography of innovation activity in Europe is the low level of innovation in many Southern European regions. Several factors contribute to this low level of innovation in Southern Europe, like industry structure (e.g., low degree of industrialization, low-tech industries), fragmented innovation systems, inadequate public R&D investment, bureaucratic inefficiencies in public administration, and relatively weak institutions (for a nuanced discussion, see the contributions in Fonseca & Fratesi, 2017). Empirical evidence indicates that these regions adopt a different mode of innovation that emphasizes process innovation and also relies more on informal and tacit knowledge than on formal scientific knowledge (Capello & Lenzi, 2017).

A third significant factor that may have shaped the regional structure of innovation activity in Europe is economic integration and the increased division of labor among most European countries as members of the European Union. Specifically, the EU's general cohesion policy and efforts to create an integrated European research area may have helped align regional levels of innovation activity (Cutrini, 2019).

Several studies focusing on the development of regional innovation activity in Europe reveal significant disparities. Capello and Lenzi (2015) argue that these regional differences in innovation activity partially reflect varying innovation modes, which require specific policy measures. Barrios et al. (2019), in their analysis of the development of regional innovation activity in the EU from 2002 to 2012, identified several convergence clubs characterized by differences in initial regional conditions. Despite a clear tendency toward club convergence, the authors do not confirm general convergence in innovation activity across EU regions. Over the longer window analyzed here, the standard indicators do show aggregate convergence, and the coexistence of the two results is precisely the puzzle we take up below.

In summary, there are significant differences in the level and type of regional innovation activity across Europe when assessing shorter time periods. In the following, we analyze the pattern of innovation over the longer run.

3. Development of innovation activity in European regions

3.1 Data and measurement

This analysis examines the development of innovation activity at the regional NUTS-2 level from 2000 to 2020. It includes all countries that were member states of the European Union as of 2024, as well as Norway, Switzerland, and the UK. The study covers 286 NUTS-2 regions and 6,006 region-year observations.

The primary indicator of innovation activity used in this analysis is the number of European Patent Office (EPO) patent applications, sourced from the OECD RegPat database. While using patent data as a proxy for regional innovation activity has limitations (as noted by Griliches, 1990, and Nagaoka et al., 2010), it remains one of the few available indicators that enable comparative analysis of innovation across regions and countries over extended periods. Some limitations of patent data include the fact that patents only represent the initial stage of the innovation process. Additionally, not all firms or inventors file patents to protect their intellectual property (as discussed by Blind et al., 2006), which can lead to underrepresentation of certain industries and areas. Furthermore, some inventors may obtain multiple related patents for essentially the same invention to prevent competitors from obtaining subsequent patents.

Despite these challenges, patents are currently the best available indicators for comparing the geographic distribution of innovation activity. EPO patent applications include the application date and the names and addresses of the applicants and inventors, enabling regional analysis over time. Patents are assigned to NUTS-2 regions based on the residential addresses. In cases where multiple inventors are involved in a patent, the patent is evenly divided among them. Regions that, according to the NUTS-2 classification, are part of Europe but are not physically located within it, or that are classified as autonomous, are excluded from this analysis (see Table A1 in the Appendix).

There is also another critical issue in the database. Some NUTS-2 regions consist solely of a city, with no surrounding areas.⁵ This means that if an inventor works in the city but lives in an adjacent region, their patent will be wrongly assigned to the adjacent region, resulting in an inaccurate patent count for the city. However, merging NUTS-2 regions comprising just a city with adjacent NUTS-2 regions can create rather large geographic units that also fail to represent the respective functional relationships adequately; the mismatch between administrative regions and functional urban areas is a well-documented source of measurement error in comparisons of European regional performance (Dijkstra, Garcilazo & McCann, 2013). For our analysis, we decided not to merge city NUTS-2 regions with adjacent regions. Robustness checks explicitly show that our results are robust to the definition of larger geographic units.⁶

Since our regional framework includes Eastern European countries that experienced socialist regimes until around 1990, we exclude the decade before 2000 to avoid potential “transition noise” in these post-socialist countries that could affect our results.⁷

To account for variability in annual patent counts, we use a 3-year moving average of patent applications per million population. Patent counts tend to be highly volatile, particularly in regions with relatively few patents, where single-year

⁵ Examples are Berlin, Hamburg, Prague, Vienna, Budapest, and Sofia.

⁶ Merging each of the sixteen city NUTS-2 regions with the adjacent regions that form its functional area reduces the sample from 286 regions to 270 units and leaves every conclusion of this paper intact: the unconditional convergence coefficient is unchanged at -0.0288 (half-life 23.7 years), dispersion falls by almost the same amount, the BIC again selects two clubs, the between-club share of total variance again barely moves (70.5% to 66.4%), and 88% of the lagging units remain in the lagging club. The merger shifts the boundary between the clubs, i.e., the merged units absorb their city’s patent intensity, so the advanced club grows from 168 to 187 units. The gap between club means widens from 11.9:1 to 17.8:1, which is the reason we prefer the unmerged NUTS-2 units in the main specification. Table A2 in the Appendix presents the full comparison.

⁷ To ensure the robustness of our results and to rule out deviations caused solely by extreme values in specific start and end years, we conducted analyses over slightly different time spans, such as 2000-2019 and 2001-2020. These alternative time spans did not yield any significant differences in the results.

fluctuations can appear disproportionately large. By averaging over three years, we reduce this volatility and make underlying trends more visible.⁸

3.2 Regional patent activity: 2000 vs 2020

Figure 1 (Panel A) illustrates the geographic distribution of patenting in Europe in the year 2000. Eastern European regions exhibited markedly low patent intensity, averaging only 3.2 patent applications per million people. In contrast, Western and Northern Europe averaged 147.7 patent applications per million population. Southern European regions also exhibited low patent activity, with an average of 22.3 patent applications per million population.

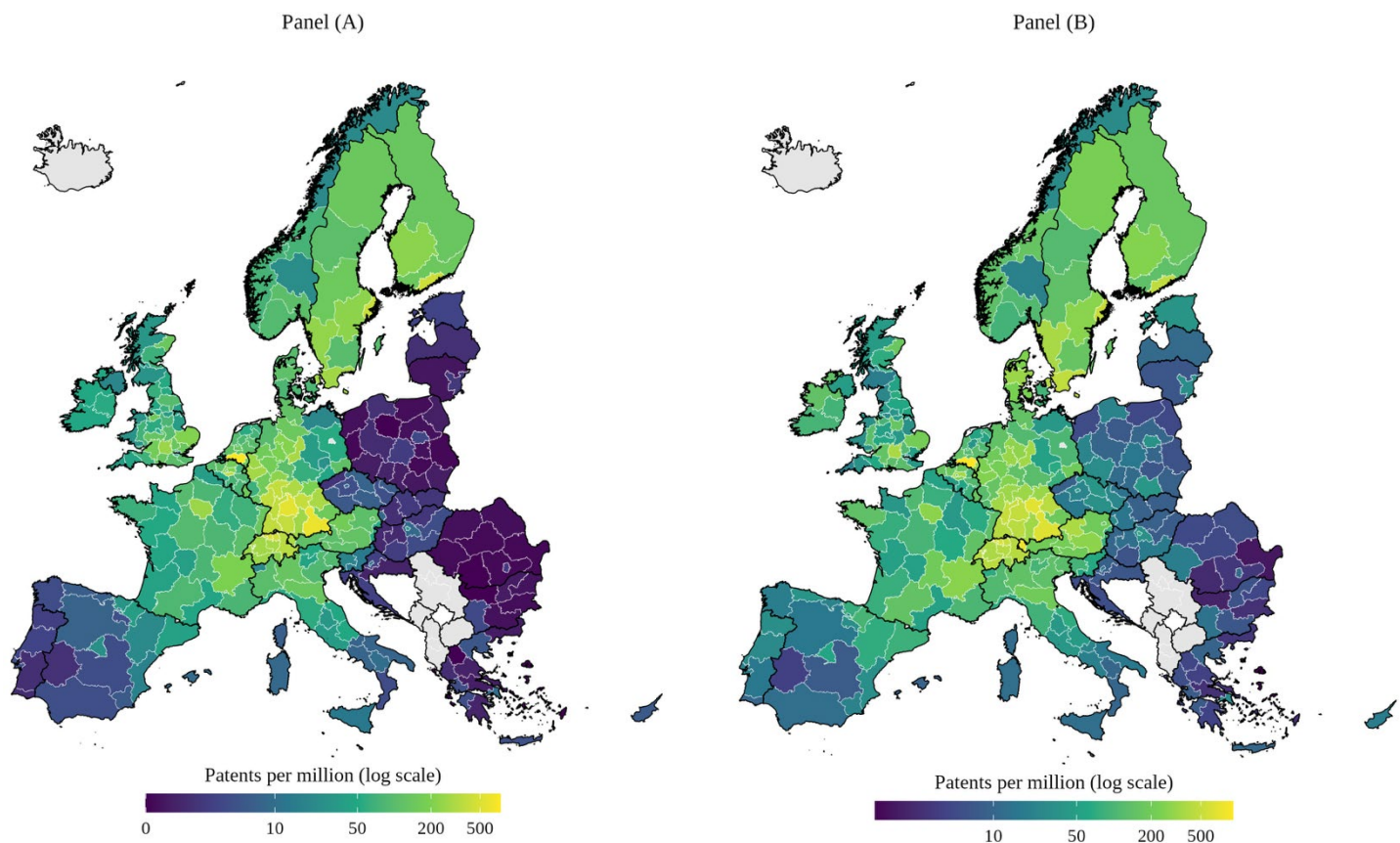


Figure 1: Patent intensity by NUTS-2 region in 2000 (Panel A) and in 2020 (Panel B) for EU countries plus Norway, Switzerland, and the UK

⁸ Since our data is reliable only up to 2020, we cannot compute a centered 3-year moving average for the final year. To address this, we employ a lagged-window approach, in which the value for year t is calculated as the average of years t , $t-1$, and $t-2$.

Table 1: Regional patent intensity by region type, 2000 and 2020

Region type	Number of regions	Filing year	Mean patents per million	Median patents per million	Standard deviation patents per million	Minimum patents per million	Maximum patents per million
Western & Northern Europe	160	2000	147.7	106.0	124.7	6.4	727.4
Western & Northern Europe	160	2020	186.8	137.9	163.2	11.7	900.4
Eastern Germany	7	2000	51.8	48.2	31.0	20.7	113.9
Eastern Germany	7	2020	95.2	79.8	52.3	41.2	193.4
Eastern Europe	61	2000	3.2	1.4	5.4	0.0	32.3
Eastern Europe	61	2020	17.3	10.3	17.8	0.8	93.0
Southern Europe	58	2000	22.3	7.4	32.5	0.0	139.6
Southern Europe	58	2020	40.0	21.7	44.2	0.3	198.4

Panel B of Figure 1 illustrates the geographic distribution of patent filings in the year 2020. This distribution has undergone a notable shift. Over the 20 years analyzed, the average number of patent applications per million people has increased to 186.8 in Western and Northern Europe. In contrast, Eastern Europe has a significantly lower average of just 17.3, while Southern Europe stands at 40.0 (see Table 1). In the following section, we analyze regional convergence using standard statistical measures.

4. Are the levels of regional patenting converging?

4.1 Beta- and Sigma convergence

Beta convergence refers to the phenomenon in which lagging regions grow faster than their more advanced counterparts. We estimate the standard panel convergence equation developed by Barro and Sala-i-Martin (1992).

$$g_{i,t} = \alpha_t + \beta \ln y_{i,t-1} + \gamma' \mathbf{X}_{i,t} + u_{i,t},$$

where $g_{i,t}$ represents the annual growth rate of log patent intensity in the region i , $\ln y_{i,t-1}$ refers to its one-year lag, while α_t denotes year fixed effects, and $\mathbf{X}_{i,t}$ is a

vector of steady-state controls. A negative value of β indicates beta-convergence, meaning that regions with lower initial patent intensity tend to grow faster on average. The implied half-life, denoted as $H = -\ln 2 / \ln(1 + \beta)$, is the time required to reduce a unit deviation from the long-run mean by half (Allington & McCombie, 2007).

We present three specifications in our analysis. Model 1 is an absolute (unconditional) regression that includes only year fixed effects. In this model, identification is based on cross-regional variation in initial patent intensity. Model 2 employs the conditional Barro/Mankiw–Romer–Weil specification (1992). In this model, we introduce region-type dummies (Eastern Europe, Southern Europe, East Germany), with Western and Northern Europe as the omitted benchmark.

Additionally, we include several variables: log GDP per capita (measured in purchasing power standard), population density, distance from the Blue Banana corridor (Brunet, 1989), and the European Quality of Government Index (EQI). The EQI, constructed by Charron et al. (2015, 2022) from large-scale citizen surveys conducted in 2010, 2013, 2017, and 2021, measures perceptions of impartiality, quality, and corruption levels within regional public services such as education, healthcare, and law enforcement. We linearly interpolate the EQI between survey waves and use the most recent available data for 2020. These variables are intended to control for differences in regional steady states. Model 3 introduces an interaction term between welfare level and region type, allowing the speed of convergence to vary across the four regional groups. Throughout the analysis, standard errors are clustered at the regional (NUTS-2) level.⁹

⁹ We intentionally omit region-level fixed effects (NUTS-2) in our main models for the following reason: beta convergence examines whether regions that initially had low patent intensity have since experienced faster growth than regions with high patent intensity. In other words, we are investigating whether lagging regions are catching up to the leaders. Since beta convergence focuses on differences between regions based on their starting levels, fixed effects, which operate by subtracting a region's time-series average from its observations, eliminate the very interregional variability we wish to analyze. As a result, a model using fixed effects no longer measures the catch-up process between leaders and lagging regions; instead, it assesses whether each region returns to its long-run average. This represents a fundamentally different issue.

Table 2: Beta-convergence results

Model	β convergence coefficient	Standard error	p-value	Half-life
1: Unconditional	−0.0288***	0.0022	<0.001	23.7
2: Conditional	−0.0513***	0.0084	<0.001	13.1
3: Heterogeneous (by region type)	−0.0183***	0.0040	<0.001	37.6

Notes: All models were estimated using Ordinary Least Squares (OLS) with year fixed effects on annual region-year observations from 2000 to 2020. Standard errors were clustered at the NUTS-2 level. The significance levels are indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The half-life (H) is calculated as $H = -\log(2) / \log(1 + \beta)$. The total number of observations amounts to 5,720. Model 2 includes region-type dummies (Eastern, Southern, East Germany; Western and Northern Europe are omitted), log of GDP per capita (PPP), log of population density, distance from the Blue Banana corridor, and the European Quality of Government Index. Model 3 further interacts the lagged log of patent intensity with the region-type dummies. Full coefficients are provided in Table A3 in the Appendix.

Table 2 presents the findings of our analysis. In Model 1, we observe an absolute beta of −0.029, which is statistically significant at the 1% level. This result indicates that regions that were initially lagging experienced significantly faster development, on average, than those that were initially advanced. The implied half-life for this effect is 23.7 years. Figure A1 in the Appendix plots the underlying cross-section: growth over 2000–2020 against the initial level, by region type.

In Model 2, we introduce region-type dummies and the steady-state controls mentioned earlier. We also use the straight-line (great-circle) distance from each region's centroid to the innovation corridor as a time-invariant indicator of proximity to the core of innovation activity in Europe.¹⁰ The full set of coefficients for Models 1–3 can be found in Table A3 of the Appendix.

The conditional convergence coefficient is highly statistically significant and is somewhat larger in absolute value than the unconditional coefficient. This suggests

The situation is further complicated by two factors: the model specification has a downward systematic error described by Nickell (1981), which applies to dynamic panels with a short time dimension. It also accounts for all time-invariant covariates (such as region type and distance from the Blue Banana corridor), which eliminates variables of direct interest. Nevertheless, as a robustness check we also estimated a two-way (region and year) fixed-effects specification. It yields $\beta = -0.213$ (SE 0.025, $p < 0.01$), which is not directly comparable to Table 2: it measures within-region mean reversion rather than catch-up between regions, and it is downward-biased in short-T dynamic panels (Nickell, 1981).

¹⁰ See Faggian (2018) for a similar application in the context of migration.

a shorter half-life for convergence. This pattern is typical in Barro-style regressions and indicates that, once long-run determinants are accounted for, regions tend to converge to their steady states more quickly than they would otherwise.

In Model 3, the speed of convergence is allowed to vary by region type. Eastern European regions converge significantly faster than the Western and Northern European benchmark. Southern European regions also converge more quickly, but at a slower rate than the Eastern regions. However, the difference in convergence speed between Eastern and Southern Europe is not statistically significant at conventional levels ($p = 0.11$), so the faster convergence in the East should be interpreted with caution.

While beta convergence measures whether lagging regions are catching up more quickly, sigma convergence assesses whether the overall dispersion of innovation activity is decreasing over time; beta convergence is a necessary but not sufficient condition for sigma convergence (Furceri, 2005). Between 2000 and 2020, the standard deviation of the logarithm of patent intensity declined by 33.8%, indicating sigma convergence.

4.2 Within-country convergence

The previous section established that European regions are converging at the European level. A further question arises: are similar convergence trends observed within individual countries? To address this, we re-estimated the unconditional Barro–Sala-i-Martin regression from Model 1 by adding country fixed effects to the year fixed effects. The country fixed effects account for all permanent differences in steady-state innovation levels between national innovation systems (e.g., national R&D policies, education systems, and the size of domestic markets), allowing the remaining variation to reflect the catch-up trends between regions within the same country. Country-by-country results are reported in Table A4 in the Appendix.

The within-country coefficient ($\beta = -0.0441$; half-life = 15.4 years) is about 1.5 times as large in absolute value as the cross-country coefficient from Model 1 ($\beta = -0.0288$; half-life = 23.7 years). A larger absolute beta indicates faster

convergence, meaning that within national borders the gap between advanced and lagging regions closes approximately 1.5 times faster.

To investigate this further, we conducted separate beta-convergence regressions for each country, dividing Germany into its eastern and western parts, and supplemented these with a sigma-convergence measure. This measure was calculated as the change in the standard deviation of the logarithm of patent intensity between 2000 and 2020 (see Panel C of Figure 3). The results indicate varying trends within individual countries. Regions in Bulgaria, Croatia, Greece, Hungary, Italy, Poland, Switzerland, and West Germany exhibit statistically significant convergence in their beta coefficients, along with a narrowing of the spread, indicating a clear pattern of catching up within these countries. A further group of countries, among them Denmark, France, Portugal, Romania, Slovakia, and Spain, shows negative coefficients that do not reach conventional significance levels.

In Austria, by contrast, the beta coefficient is positive and statistically significant, which means that the leading regions have measurably extended their lead. Finland, the Netherlands, Norway, and Sweden point in the same direction with positive but statistically insignificant coefficients. These countries already have a high and relatively uniform level of innovation, leaving little room for internal catch-up dynamics.

Overall, both across individual European countries and within them, most evidence points to a trend toward harmonization over time, although the pace and scale of this convergence vary considerably. These findings confirm convergence when evaluated using standard indicators. However, as we will demonstrate in the next section, these reassuring aggregate figures mask a more complex picture.

5. Persistence patterns and the illusion of convergence

The analysis presented above shows that regions that are currently lagging are developing more quickly than the leaders, overall disparities are decreasing, and all standard indicators of convergence suggest a trend toward narrowing the gap: lagging regions appear to be catching up with the frontrunners. However, this assessment,

while technically accurate, can be misleading. Despite overall convergence there is a rigid two-group structure that has remained largely unchanged over the past two decades. While lagging regions have improved their situations in absolute terms, it largely occurs within a stable structural divide. Put differently, for most lagging regions, the catching-up indicated by conventional statistics has not led to a real change in their relative position.

5.1 Two clubs in European regional innovation

The convergence statistics discussed in Section 4 consider all regions as part of a single distribution that converges to a common equilibrium state. However, the distribution of regional patent intensity is not unimodal; it is distinctly bimodal. There is a clear separation between a large group of regions with high patent intensity and another large group with low patent intensity (see Figure A2 in the Appendix). This bimodality suggests that European regions may be converging not toward a single equilibrium state but rather toward two distinct states, which aligns with the convergence club hypothesis developed in the context of GDP and income (Quah, 1996, 1997; Durlauf & Johnson, 1995).

To empirically identify these clubs, we employ Gaussian mixture models (GMM), a probabilistic clustering method that fits a finite mixture of Gaussian distributions to the cross-sectional distribution of regional patent intensity (McLachlan & Peel, 2000; Fraley & Raftery, 2002). The number of components and the form of the component covariance matrices are determined by minimizing the Bayesian information criterion (BIC; Schwarz, 1978). BIC penalizes model complexity, which helps prevent overfitting that may occur by simply increasing the number of mixture components. We use the average patent intensity only for the period 2010 to 2020 in this procedure to capture the latest developments in convergence and persistence patterns.

We utilize the GMM/BIC approach because, unlike simple cut-offs such as median or tercile splits, it allows the data to determine how many sub-populations exist and where their boundaries lie. This method produces posterior membership

probabilities instead of arbitrary cut points. However, we verify that our findings are not merely an artifact of this methodological choice: a simpler classification based on bottom-tercile rankings yields very similar club assignments and overlaps with the GMM results; the two classifications assign 92% of regions to the same club.

The optimal solution identified by the BIC index categorizes regions into two clubs, as shown in Table 3. The advanced club comprises 168 regions with an average patent intensity of 185 applications per million inhabitants. In comparison, the lagging club comprises 118 regions with a much lower average of just 16 applications per million inhabitants. This results in a significant gap between the two clubs' averages, with a ratio of 12:1.

The geographical makeup of these groups is quite pronounced (see Table 3). The advanced club is predominantly composed of regions in Western and Northern Europe (85%), with only a small representation from Southern Europe and Eastern Germany. In contrast, the lagging club is more evenly divided between Eastern Europe (47%) and Southern Europe (34%), with minimal representation from Western and Northern regions. Notably, only 2 out of 57 regions in Eastern Europe are part of the advanced club. This geographical distribution closely reflects the historical division of Europe into a center and a periphery, with the socialist era playing a particularly significant role in shaping these dynamics.

Eastern Germany holds a unique position in regional development. Six of the seven NUTS-2 regions in Eastern Germany are classified as advanced, accounting for 4 percent of this category. Only Mecklenburg-Vorpommern falls into the lagging group, which still contrasts with the broader context of post-socialist Europe, where only 2 of 57 Eastern European regions are classified as advanced. From a pan-European perspective, Eastern Germany has clearly distanced itself from the periphery, typically characterized by low levels of innovation. This transformation can be attributed to three decades of integration into the West German innovation

Table 3: Convergence club summary statistics and geographic composition

Club / Region type	Number of regions	Mean patents per million	Median patents per million	Standard deviation patents per million	Minimum patents per million	Maximum patents per million
<i>Advanced</i>	168	185	135.7	143.9	48.5	730.4
of which: East Germany	6 (3.6%)	104.5	100.5	44.5	48.9	173.6
of which: Eastern Europe	3 (1.8%)	64.5	60.7	8.6	58.4	74.3
of which: Southern Europe	16 (9.5%)	98.1	87.9	37.1	51.6	176.3
of which: Western & Northern Europe	143 (85.1%)	200.6	154.3	149.9	48.5	730.4
<i>Lagging</i>	118	15.6	11.1	12.6	0.3	45.9
of which: East Germany	1 (0.8%)	44.5	44.5	Not applicable	44.5	44.5
of which: Eastern Europe	58 (49.2%)	11.8	9.0	9.8	0.6	40.4
of which: Southern Europe	42 (35.6%)	13.1	10.1	10.1	0.3	42.2
of which: Western & Northern Europe	17 (14.4%)	33.1	34.7	10.8	10.2	45.9

Notes: Club assignment based on Gaussian mixture models (BIC-optimal $K = 2$) applied to mean patent intensity over 2010–2020. Sub-rows show geographic composition within each club. Patents per million = EPO patent applications per million population (3-year moving average).

system, significant federal financial support, and the re-establishment of universities and public research institutes. As a result, the region's patent intensity has reached levels comparable to those in the West.

However, this does not imply that the divide between Eastern and Western Germany has disappeared. When Eastern German regions are compared with their West German counterparts, they still fall behind. Research by Fritsch et al. (2025) indicates that since reunification, innovation activity in the two parts of the country has tended to diverge rather than converge, reflecting the enduring impact of the socialist era.

For this reason, throughout this study, we will treat Eastern Germany as a distinct category. While it may appear 'advanced' by European standards, it still does not match the national innovative frontier established by West Germany.

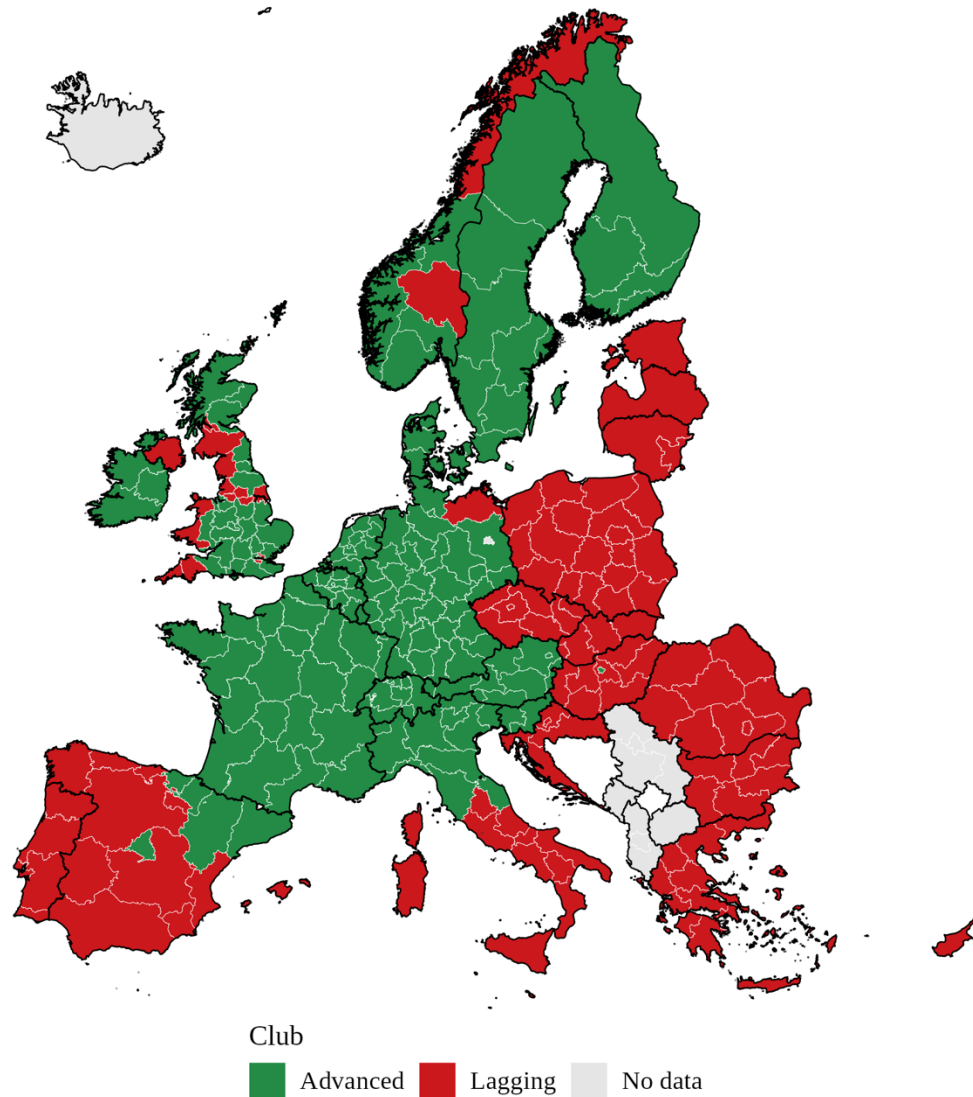


Figure 2: Convergence clubs in European regional innovation

The geographic distribution of club membership across Europe is illustrated in Figure 2. The advanced club forms a continuous core that stretches from the British Isles through the Benelux countries, Germany, Scandinavia, and France, with branches extending into northern Italy and northeastern Spain. The lagging club includes nearly all of Eastern Europe, most of Southern Europe, and the peripheral regions of Western Europe.

5.2 The convergence illusion

Given the two-club structure, the central question is whether the aggregate convergence described in Section 4 truly reflects a narrowing of the structural gap in innovation activity across European regions, or if this alignment occurs primarily within individual clubs while the overall gap remains unchanged. To address this question, we decompose the total variance in regional patent intensity into inter-club and intra-club components using standard ANOVA, tracking this decomposition annually over the entire observation period from 2000 to 2020.

Table A5 in the Appendix reconciles all standard convergence indicators with the evidence at the club level. These indicators which include beta convergence, sigma convergence, the proportion of variance between clubs, and the absolute difference between club means suggest convergence is occurring. Lagging regions are catching up more rapidly (the half-life is 11 years), overall dispersion is decreasing, and the gap between club means has narrowed. At first glance, this seems to indicate a genuine process of catching up.

However, a closer analysis reveals this to be an illusion. The share of variance between the two clubs has not fallen at all. We observe 67.7% in 2000 and 67.1% in 2020, and it still accounts for more than two-thirds of the total inequality. In other words, despite two decades of growth in lagging regions, the two-club structure remains the dominant characteristic of regional innovation in Europe. The decline in total variance primarily stems from greater similarity within each group: lagging regions are becoming more alike, and a similar trend is evident among advanced regions. The gap between the two clubs narrows only in relative terms; measured in patents per million, as shown in Panel A of Figure 3, it continues to widen.

Figure 3 illustrates four dimensions of this paradox. Panel A shows the evolution of mean patent intensity for each club. The mean intensity of the advanced club rises strongly and continuously throughout the 2000–2020 period, while the lagging club also increases, but from a much lower baseline and at a significantly slower pace. In absolute terms, the gap in patents per million between the clubs has widened, with the two lines diverging; Figure A3 in the Appendix shows the same

two series with confidence bands. This clearly demonstrates that, in absolute terms, the innovation gap between the two clubs has not narrowed; in fact, it has grown.

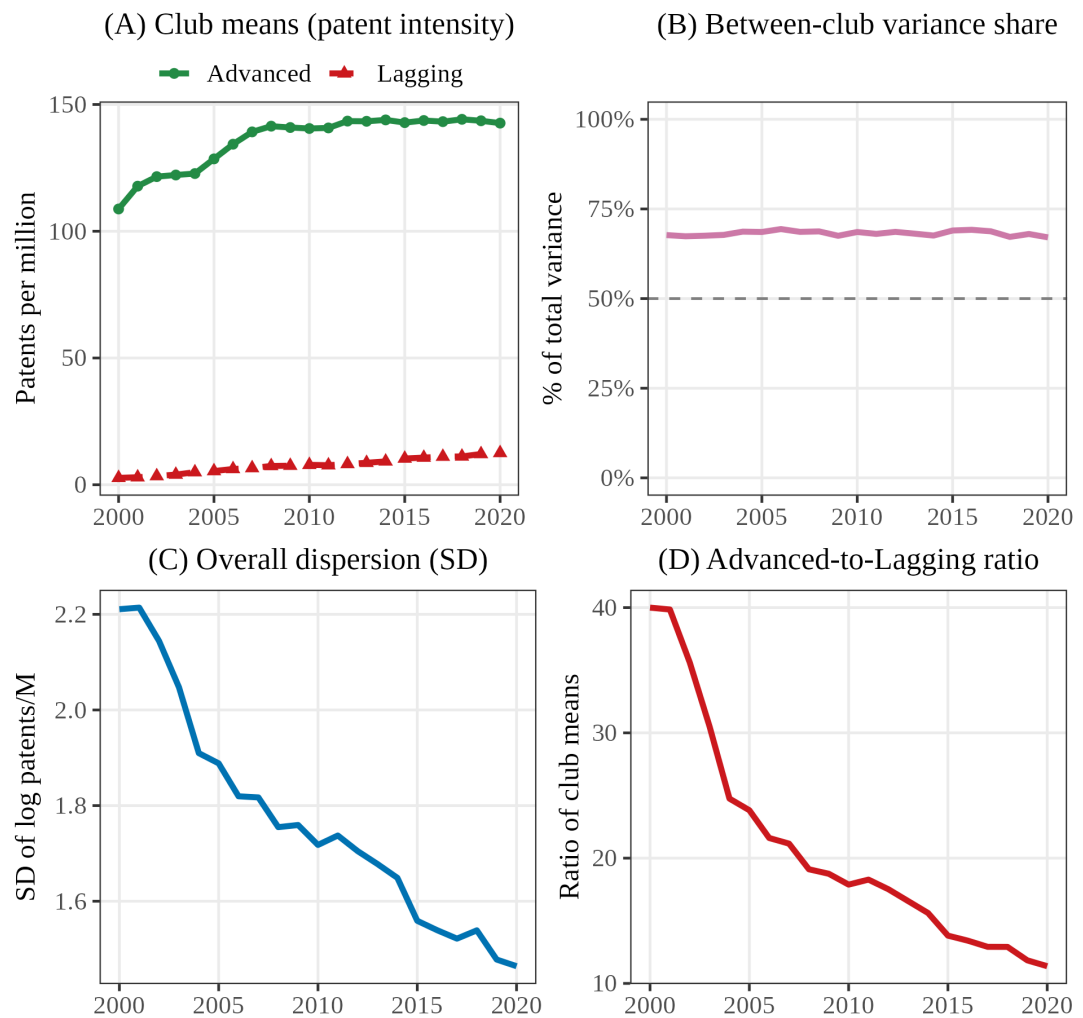


Figure 3: The convergence illusion

Panel C illustrates overall sigma-convergence, showing that the cross-sectional standard deviation of log patent intensity consistently declines even as club averages diverge. This occurs because of intra-club homogenization, in which

lagging regions cluster around a low mean, while more advanced regions become increasingly similar to one another.¹¹

Panel B presents the between-club share of the total variance from the ANOVA decomposition. Despite two decades of aggregate convergence, the between-club component has not declined, remaining at 67.1% and close to 70% throughout the period. This two-club structure continues to account for the majority of total regional inequality in European innovation. Figure A4 in the Appendix shows the between- and within-club shares side by side over the whole period. The structural divide has not weakened at all over the two decades.

Panel D displays the ratio of mean patent intensity, calculated as the advanced club mean divided by the lagging club mean. This ratio sharply decreases from approximately 40:1 in the early 2000s to about 12:1 by 2020. However, the lagging club started with very few patents. Specifically, the lagging club increased from around 1–2 patents per million to about 16, which represents a small absolute gain but a substantial reduction of the ratio. Hence, Panel D rather reflects a convergence illusion.

The Phillips and Sul (2007) log-t test complements the beta-convergence analysis in Section 4.1 by evaluating whether regions converge towards a common transition path. It uses a sigma-type criterion to assess the decrease in internal dispersion. In contrast to beta-convergence, which examines whether less-innovative regions are growing more rapidly, the log-t test indicates that the entire sample is diverging ($b = -0.237$, $t = -3.78$). Table A6 in the Appendix reports the test for the full sample and for each club separately.

When applied to individual clubs, the results highlight a stark asymmetry (Panel A, Figure 3). The lagging club exhibits convergence ($b = 0.428$, $t = 3.17$), reflecting both rapid growth from lower starting points and increasing homogeneity.

¹¹ Sigma-convergence reflects consolidation within clubs rather than convergence across clubs. This limitation was noted by Quah (1996), who pointed out that a decreasing standard deviation indicates the spread of the distribution but does not capture its shape, meaning it can decline even as the distribution becomes polarized into distinct groups.

In contrast, the advanced club combines within-club beta-convergence (Table A7) with log divergence ($b = -0.865$, $t = -24.82$), as leading regions pull ahead, widening internal disparity. This duality of beta-convergence alongside rising dispersion explains the net convergence observed in Section 4, despite persistent structural divides.

Supporting this, within-club beta-convergence (Table A7) shows a half-life of ~11 years for the lagging group, signaling swift equilibration at low innovation levels, while the advanced group's half-life (~100 years) indicates negligible convergence. Thus, the narrowing in Panel A stems from rapid homogenization within the lagging club, not from bridging the structural gap.

5.3 Club persistence and transitions

To assess whether the structural division of European regions is diminishing, we can look at whether regions change clubs over time. We compute each region's average patent intensity for two distinct periods, the early period (2000–2009) and the late period (2010–2020), and classify both averages against the same threshold: the decision boundary of the Gaussian mixture model estimated in Section 5.1, which lies at 47.8 patents per million. Applying that boundary to the 2010–2020 averages reproduces the club membership in Table 3, region by region, so the transition matrix and the club map describe the same structure. Holding the threshold fixed is essential here. A classifier re-fitted inside each sub-period measures movement against a boundary that rises with the distribution, so that when every region improves, none can cross it. Under that rule, the lagging club retains 100% of its members by construction. The resulting transition matrix is reported in Table A8 in the Appendix.

Of the regions classified as lagging in the early period, 89.7% remained in the same category during the second period. Advanced regions are even more immobile: 96.9% of those classified as advanced initially retained that status. Thirteen regions (10.3% of the lagging group) moved up to the advanced club over two decades, while 5 previously advanced regions fell behind. Roughly nine in ten regions, therefore, never change clubs. A total of 54% of the regions (155 regions) are consistently

‘advanced’, while another 40% (113 regions) are consistently ‘lagging’. The remaining 6% are the movers: 13 regions escaped the ‘lagging’ category, and 5 previously ‘advanced’ regions fell behind.

This remarkable persistence emphasizes the illusion of convergence. lagging regions experienced faster growth, and disparities between regions decreased. However, this improvement took place within a largely unchanged framework: while nearly all lagging regions advanced in absolute terms, only about one in ten managed to cross the threshold separating the two groups. This is because aggregate convergence primarily results from increased similarity within groups. This process occurs rapidly in lagging regions, with a half-life of approximately 11 years, whereas it is barely detectable in advanced regions, which have a half-life of around 100 years. As a result, the gap between the two groups remains essentially the same.

Persistence, in this context, refers to club membership rather than absolute progress. The roughly 90% of regions that remain in the lagging group are not stagnant; as shown in Panel A of Figure 3, nearly every lagging region increased its patent intensity from 2000 to 2020. However, because the club threshold is significantly higher than their initial levels, even substantial gains are insufficient to cross the structural divide.

Figure A5 in the appendix illustrates four development trajectories within Europe, and this finding is among the most significant results of our analysis. The thirteen regions that break away from the lagging group are not randomly distributed. Most of them either adjoin the advanced core (i.e., Leipzig and Saxony-Anhalt next to the German core, Nord-Pas-de-Calais and Aquitaine within France, the Basque Country and Aragón beside Catalonia, and both Slovenian regions on the Austrian and Italian border) or are capital regions in their own right, namely Madrid and Budapest. Movement in the opposite direction is even more concentrated: all five regions that fall out of the advanced club are in northern England (Cumbria, Greater Manchester, Lancashire, East Yorkshire, and Northern Lincolnshire, and West Yorkshire), an old industrial belt losing ground relative to a rising threshold. Regions that remain persistently behind are located in peripheral areas, far from the core.

This geography of “escape” aligns closely with the center-periphery model of regional development (Iammarino, Rodríguez-Pose, and Storper, 2019; Rodríguez-Pose, 2018). Being close to innovation leaders fosters knowledge exchange, facilitates supply chain connections, and provides access to the labor market. These elements are crucial for regions seeking to catch up economically. Additionally, all of these factors rely on the supporting infrastructure and interregional links that connect a region to its core (Crescenzi & Rodríguez-Pose, 2012). Conversely, a greater distance from the center reinforces a “lock-in” effect.

Finally, we account for different historical legacies that affect lower innovation activity, as discussed in section 2.2. To this end, we distinguish between Southern Europe and post-socialist Eastern Europe. The Eastern and Southern European regions display significant differences in their dynamics within the lagging club. The Phillips–Sul test, applied separately to both subgroups (see Table A9 in the Appendix), reveals that the lagging regions of Eastern Europe experience strong internal convergence ($b = 0.90$, $t = 5.86$), with an average annual growth rate of 2.2%. In contrast, the lagging regions in Southern Europe show ambiguous convergence ($b = -0.154$, $t = -0.93$), with a lower growth rate of just 1.2%. Figure A6 in the Appendix plots the average patent intensity of the two sub-groups: The Eastern regions start far lower and catch up with the Southern ones by the end of the period.

The lagging regions of Southern Europe show much lower growth and weaker internal convergence. These regions appear to be more deeply entrenched in a low-innovation equilibrium. This observation aligns with our finding that Eastern European regions are approaching the innovation frontier at a significantly faster pace than their southern counterparts (as discussed in Section 4). Nevertheless, the club analysis indicates that even the faster-growing regions in Eastern Europe have, for the most part, not yet escaped the lagging club.

5.4 Robustness: EU member states only

Our sample includes Norway, Switzerland, and the United Kingdom, as well as the EU member states. Since the policy conclusions concern EU cohesion and innovation policy, we re-ran the entire analysis on the 232 NUTS-2 regions of the EU member states alone. The results are similar. The unconditional convergence coefficient is -0.0293 , compared with -0.0288 in the full sample; dispersion falls from 2.334 to 1.539, and the BIC again selects exactly two clubs: of 129 advanced and 103 lagging regions. The between-club share of total variance is, if anything, higher and more rigid than in the full sample: 75.1% in 2000 and 71.3% in 2020. Club membership is again almost perfectly persistent, with 92.0% of lagging regions and every advanced region keeping their status. Table A10 in the Appendix reports the comparison indicator by indicator, and Figure A7 reproduces the four panels of Figure 3 for the EU-only sample. The convergence illusion is therefore not an artefact of including three non-member countries.

6. Conclusions

This paper examined the dynamics of regional innovation activity in Europe from 2000 to 2020. The analysis leads to three main conclusions. First, all standard measures indicate that European regions are converging in terms of innovation performance. Beta convergence is statistically significant, sigma convergence shows a steady decline in dispersion, and average annual growth rates are highest in regions that were initially lagging. Eastern European regions are converging more rapidly than Southern European regions, but both groups demonstrate positive absolute growth. A similar pattern of convergence can be observed in most European countries, with exceptions including Austria, Finland, the Netherlands, Norway, and Sweden.

Second, the overall picture of converging innovation activity in Europe is somewhat misleading. A deeper investigation suggests that European regions are divided into a persistent two-club structure. One group consists of 168 ‘advanced’ regions, while the other comprises 118 ‘lagging’ regions. The gap in patent intensity

between these two groups is 12:1. The between-club component accounts for over 60% of the total variance throughout the observation period. Club membership remained virtually unchanged; approximately 90% of lagging regions continued to lag, while 97% of advanced regions retained their status.

Third, the lagging regions do not constitute a homogeneous group. Eastern European regions in the lagging club are developing more rapidly, probably reflecting the dynamics of post-socialist transformation and EU integration. In contrast, the lagging regions of Southern Europe show weaker internal convergence and slower growth, consistent with long-standing structural barriers.

Altogether, while standard metrics (beta, sigma) suggest European regions are converging in innovation, the underlying two-club structure remains rigid, with no meaningful reduction in the structural divide. This calls for more targeted, club-specific policies to address persistent disparities. In contrast, Barrios et al. (2019), in their analysis of the development of regional innovation activity in the EU for a shorter time period between 2002 to 2012, identified several convergence clubs characterized by differences in initial regional conditions. Despite a clear tendency toward club convergence, the authors do not confirm general convergence in innovation activity across EU regions. Hence, our results suggest that including a longer time horizon could make a difference for the assessment of convergence patterns. This contribution also calls for monitoring long-term trends in future research.

This study advances the literature on regional convergence and innovation by revealing nuanced, club-based dynamics that challenge the conventional narrative of uniform progress. While existing research on income convergence often emphasizes beta- and sigma-convergence (e.g., Barro and Sala-i-Martin, 1992; Quah, 1996) as evidence of narrowing disparities, our findings align with more recent work from innovation research highlighting persistent polarization in innovation (e.g., Capello & Lenzi, 2015, 2017; Barrios et al., 2019).

We also contribute to the debate on historical legacies for innovation activity (e.g., Radosevic, 2002, 2022; Fritsch et al., 2025) by zooming into differences across lagging regions in Eastern and Southern Europe. In Eastern Europe, slow convergence towards the innovation frontier may be influenced by inhibiting factors and by the turbulence and disruptions that characterized the transformation process, which may be exacerbated by the potential erosion of democracy in some countries. Conversely, in Southern Europe, persistently low innovation activity aligns with long-standing descriptions of a north-south divide in countries such as Italy, indicating structural factors that predate EU integration and may require different policy responses.

Furthermore, our results suggest that in Eastern Europe, the post-socialist transition has outlined a growth path that, if sustained, may eventually allow some countries to move into the advanced club. In this case, the priority is to consolidate and extend this growth trajectory. It is crucial to shift the current catch-up process, primarily driven by EU integration, foreign direct investment, and the absorption of imported knowledge, into a foundation for local innovation potential. This transformation ensures that economic growth does not stall once these external drivers diminish.

In contrast, Southern European regions face more structural challenges that cannot be solved merely by increasing research and development spending. Slow economic growth and weak internal convergence indicate deep-rooted issues, including fragmented regional innovation systems, limited absorption capacity, and significant shortcomings in the quality of regional governments, all of which undermine the effectiveness of public investment (Charron et al., 2015; Rodríguez-Pose, 2018). For these regions, targeted policies that enhance institutional quality, governance, and the connections between businesses, universities, and the public sector are likely to be more important than the overall scale of innovation funding. Treating both groups as a single category of "lagging regions" would obscure the reality that one group needs assistance to maintain its current pace of development, while the other needs support primarily to establish that pace in the first place.

Our findings have direct implications for EU innovation policy. Cohesion policy and smart specialization strategies have contributed to an overall increase in innovation levels, which is an important achievement. However, our analysis indicates that this broad-based growth has not changed the two-tier structure of regional innovation in Europe and the EU. To bridge gaps between different groups, approaches that account for the specific constraints of disadvantaged regions are likely to be more effective than a one-size-fits-all strategy. The European Regional Innovation Scoreboard (European Commission, 2025) highlights a persistent uneven distribution of innovation performance across Europe in the early 2020s. Based on the Summary Innovation Index (SII), which aggregates 23 measures of innovation activity, the report suggests a tendency toward long-run regional convergence. Notably, it indicates that the lowest-performing regions are gradually catching up with the top performers. Whether this translates into substantial convergence is a question for future research.

Our analysis does have certain limitations. One major limitation stems from our use of patent applications as a measure of innovation activity. It is well established that patents reflect only one aspect of the innovation process (Griliches, 1990; Nagaoka et al., 2010) and may not fully capture sectors and regions where alternative forms of intellectual property protection are more common (Blind et al., 2006). Additionally, the economic value of patents varies significantly, and a patent represents the invention itself rather than its commercialization. Another limitation is that we count only applications filed with the European Patent Office (EPO) and categorize them based on the inventor's residence address. Consequently, differences between countries in their propensity to patent at the EPO and in inventor mobility may introduce measurement bias. Despite these limitations, patents remain the only widely available indicator that allows for comparisons of innovation activity between regions over longer time periods.

Several avenues for future research stem from our findings. First, the significant differences between Eastern and Southern Europe emphasize the need for a more in-depth examination of the mechanisms driving their divergent development

trajectories. Since 1990, post-socialist countries have experienced substantial transformations in their economic and innovation systems. It is important to systematically analyze how these changes have shaped, or continue to shape, their national capacity for innovation. This analysis should particularly consider the roles of foreign direct investment, institutional reform, and the quality of innovation outcomes, rather than just their quantity.

This heterogeneity within the lagging regions also raises important questions. The overall convergence we observed is asymmetric: it results from lagging regions becoming more similar to one another, while advanced regions exhibit greater internal dispersion. Whether the observed homogenization among the laggards is sustainable or merely temporary remains uncertain. If Eastern and Southern regions continue to develop at different rates, the lagging group may begin to diverge again. Therefore, tracking when and if such a split occurs would enhance our understanding of the persistence of this two-club structure.

Second, in our analysis, we used a single classification method (Gaussian mixture models) to identify convergence clusters. However, the definition and identification of development groups raise methodological issues that have significant implications for both academic research and policymaking. Different approaches, whether they are growth-based, ranking-based, hybrid, or data-driven, can yield different group assignments, leading to varying conclusions about the appropriate policy types. A systematic comparison of alternative classification methods and an assessment of the sensitivity of our results to these methodological choices would significantly strengthen the evidence base for regional innovation policy.

Third, it would be worthwhile to examine conditions in regions with the lowest levels of innovation activity to understand the reasons for their poor performance. Do these regions suffer from an “innovation trap” that hinders the development of innovation? To answer this, we need to look beyond the mere number of patents and analyze regional factors that contribute to these traps, including low absorption capacity, outflows of skilled labor, weak connections

between firms and research institutions, and institutional barriers that diminish the return on investment in innovation. Identifying which of these mechanisms is most decisive, and whether they reinforce one another, could help us determine whether there is a genuine trap holding back persistently lagging regions or whether they are simply progressing more slowly.

Fourth, the small number of regions that have escaped the lagging group and those that have fallen behind (from the advanced group) warrant closer examination. Understanding the factors that distinguish these “leapfroggers” from persistently lagging regions could provide valuable insights for policymakers. Case studies and comparative analyses that highlight the institutional, structural, and policy conditions enabling transitions between clubs would complement the aggregate patterns documented in this research.

Finally, an open question remains as to whether the convergence illusion observed in patent quantity also applies to patent quality, to innovation inputs such as R&D expenditure and personnel, and to broader measures of innovation output beyond patenting. If the two-club structure is equally persistent for high-quality patents and innovation inputs, the policy implications could be even more significant.

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Appendix

Table A1: List of regions excluded from analysis

Name and code	Explanation
Ceuta (ES63) and Melilla (ES64)	Both Spanish regions belonging geographically to North Africa
Guadeloupe (FRY1) and Martinique (FRY2)	Both French regions in the Caribbean
Guyane (FRY3)	A French region in South America
Réunion (FRY4) and Mayotte (FRY5)	Both French regions in the Indian Ocean
Região Autónoma da Madeira (PT20)	Portuguese autonomous region in the Atlantic Ocean
Região Autónoma dos Açores (PT30)	Portuguese autonomous region in the Atlantic Ocean
Cyprus (CY00)	Only includes the Greek-controlled areas of the Republic of Cyprus; the Turkish-controlled northern part (the self-declared “Turkish Republic of Northern Cyprus”) is not included in the NUTS classification as it is not recognized by the EU
Svalbard and Jan Mayen (NO0B)	Norwegian Arctic territories with no resident population and no patenting-intensity measure in any year

Table A2: Robustness (city NUTS-2 regions merged with their functional areas)

Indicator	Main specification: NUTS-2 regions	Robustness: city regions merged
Spatial units	286	270
Region-year observations (β regression)	5,720	5,400
β -convergence, unconditional	−0.0288***	−0.0288***
Implied half-life (years)	23.7	23.7
σ (SD of log patent intensity), 2000	2.211	2.209
σ (SD of log patent intensity), 2020	1.464	1.450
Number of clubs selected by BIC	2	2
Advanced club (units)	168	187
Lagging club (units)	118	83
Ratio of club means, 2010–2020	11.9:1	17.8:1
Between-club share of total variance, 2000	67.7%	70.5%
Between-club share of total variance, 2020	67.1%	66.4%
Lagging-club persistence	89.7%	87.9%

Notes: In the robustness column, the sixteen NUTS-2 regions that consist of a city without its surroundings are merged with the adjacent regions that form their functional area, reducing the number of regions from 286 to 270. Patent counts and population are summed before forming the ratio. Everything else, i.e., sample period, specification, club identification, and the transition threshold, is unchanged. *** $p < 0.01$.

Table A3: Full coefficient table for Models 1–3 (β -convergence)

Variable	1: Unconditional	2: Conditional	3: Heterogeneous
$\ln(\text{Patents per million})_{t-1}$	−0.0288*** (0.0022)	−0.0513*** (0.0084)	−0.0183*** (0.0040)
Eastern Europe		0.0400*** (0.0125)	0.2636*** (0.0216)
Southern Europe		−0.0053 (0.0104)	0.2183*** (0.0314)
East Germany		0.0040 (0.0093)	0.0814* (0.0487)
$\ln(\text{GDP per capita, PPP})$		0.0766*** (0.0200)	0.0920*** (0.0174)
$\ln(\text{Population density})$		−0.0019 (0.0028)	−0.0035 (0.0023)
Distance to Blue Banana corridor		−0.0000*** (0.0000)	−0.0000*** (0.0000)
European Quality of Government Index		0.0276*** (0.0053)	0.0301*** (0.0052)
$\ln(\text{Patents/M})_{t-1} \times \text{Eastern Europe}$			−0.0602*** (0.0068)
$\ln(\text{Patents/M})_{t-1} \times \text{Southern Europe}$			−0.0509*** (0.0093)
$\ln(\text{Patents/M})_{t-1} \times \text{East Germany}$			−0.0133 (0.0111)
Number of observations	5,720	5,720	5,720
R ² adjusted	0.068	0.080	0.96
Year fixed effects	Yes	Yes	Yes
Cluster SE	NUTS-2	NUTS-2	NUTS-2

Notes: OLS estimates of the Barro–Sala-i-Martin (1992) convergence regression with year fixed effects. Dependent variable: annual growth of log patent intensity. Cluster-robust standard errors (NUTS-2) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Region-type dummies use Western and Northern Europe as the omitted benchmark.

Table A4: Within-country beta- and sigma-convergence

Country	Number of regions	β coefficient	Half-life (years)	Standard deviation (ln pat) 2000	Standard deviation (ln pat) 2020	σ trend
Croatia	4	-0.667*	20.4	1.177	0.478	Decreasing
Greece	13	-0.511***	26.8	1.654	1.042	Decreasing
Hungary	8	-0.393*	34.9	1.120	0.817	Decreasing
Bulgaria	6	-0.315*	43.7	1.145	0.852	Decreasing
Slovakia	4	-0.438	31.3	0.820	0.582	Decreasing
Poland	17	-0.618***	22.1	0.930	0.735	Decreasing
Italy	21	-0.170**	81.2	1.086	0.969	Decreasing
Switzerland	7	-0.371**	37.0	0.301	0.206	Decreasing
West Germany	30	-0.182**	75.9	0.564	0.508	Decreasing
Portugal	5	-0.407	33.7	0.515	0.461	Decreasing
Spain	17	-0.160	86.5	0.995	0.956	Decreasing
East Germany	7	-0.103	134.7	0.560	0.529	Decreasing
France	22	-0.105	131.5	0.719	0.716	Decreasing
Czech Republic	8	-0.161	85.8	0.539	0.544	Increasing
Denmark	5	-0.236	58.3	0.521	0.582	Increasing
Sweden	8	0.040	–	0.496	0.559	Increasing
Belgium	11	-0.063	218.9	0.547	0.610	Increasing
Romania	8	-0.353	38.9	0.855	0.985	Increasing
United Kingdom	41	-0.071	195.3	0.624	0.771	Increasing
Austria	9	0.287**	–	0.463	0.611	Increasing
Netherlands	12	0.111	–	0.681	0.833	Increasing
Norway	6	0.115	–	0.692	0.847	Increasing
Ireland	3	-3.394	3.7	0.052	0.268	Increasing
Finland	5	0.309	–	0.704	0.949	Increasing

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. $\beta < 0$ indicates beta-convergence (lagging regions grow faster). Half-life is shown only for countries with $\beta < 0$. The σ trend indicates whether the within-country dispersion of log patent intensity fell or rose between 2000 and 2020. Countries are ordered by the size of that change, from the strongest decline in dispersion to the strongest increase, so that the converging and diverging groups are visible without shading. Germany is split into East and West.

Table A5: Reconciliation of convergence metrics

Metric	Result	Start value (~2000)	End value (~2020)	Interpretation
Beta-convergence (unconditional)	Convergence	–	see Table 2	Laggards grow faster on average (half-life: 24 years)
Sigma-convergence (overall SD)	Convergence	2.211	1.464	Overall dispersion declining (convergence in aggregate)
Between-club variance share	Convergence	67.7%	67.1%	Declining share (67.7% to 67.1%): clubs moving closer together
Absolute gap (club means, log)	Convergence	3.69	2.43	Gap narrowing (3.69 to 2.43 in log terms): structural divide shrinking
Gap ratio (exp of log gap)	Convergence	40:1	11.9:1	Advanced regions produce ~11.9:1 more patents per capita than Lagging (down from 40:1)
Club persistence rate	Persistence	–	–	Persistently Advanced 155 regions (54.2%); Persistently Lagging 113 (39.5%); Escaped Lagging 13 (4.5%); Fell Behind 5 (1.7%)

Notes: All metrics computed for 286 NUTS-2 regions over 2000–2020. Between-club variance share from ANOVA decomposition. Gap ratio = advanced club mean/lagging club means in levels.

Table A6: Phillips–Sul log-t convergence test

Sample	b coefficient	t-statistic	Number of regions	Number of years	Result
Full sample	−0.2370	−3.78	286	21	Divergence
Advanced club	−0.8650	−24.82	168	21	Divergence
Lagging club	0.4280	3.17	118	21	Convergence

Notes: Phillips & Sul (2007) log-t test. $b > 0$ with $t > -1.65$ indicates convergence; $b < 0$ with $t < -1.65$ indicates divergence; otherwise the result is inconclusive.

Table A7: Beta-convergence within each club

Club	β coefficient	Standard error	Number of observations	Half-life (years)
Advanced	−0.0068	0.0021	3,360	101.9
Lagging	−0.0596	0.0089	2,360	11.3

Notes: Pooled OLS within each club. Negative β indicates convergence (lagging regions grow faster).

Table A8: Club transition matrix, early period (2000–2009) vs late period (2010–2020)

Club in early period (2000–2009)	Club in late period (2010–2020)	Number of regions	Percentage
Advanced	Advanced	155	96.9%
	Lagging	5	3.1%
Lagging	Advanced	13	10.3%
	Lagging	113	89.7%

Notes: Both sub-period averages are classified against the same threshold: the decision boundary of the Gaussian mixture model used in Section 5.1, which lies at 47.8 patents per million. Applying that boundary to the 2010–2020 averages reproduces Table 3 region by region. A period-specific classifier would instead re-fit the boundary inside each sub-period, so it measures movement against a bar that rises with the distribution; under that rule, no lagging region crosses at all (persistence 100%).

Table A9: Phillips–Sul tests within lagging club sub-groups

Sub-group	b coefficient	t-statistic	Number of regions	Number of years	Result	Growth (2000–2020)
Eastern lagging	0.900	5.86	59	21	Convergence	2.202
Southern lagging	−0.154	−0.93	42	21	Inconclusive	1.244

Notes: Phillips & Sul (2007) log-t test applied separately to Eastern and Southern sub-groups within the lagging club. Growth = change in $\ln(\text{patents per million})$, 2000–2020.

Table A10: Robustness (EU member states only)

Indicator	Full sample	EU member states only
Regions	286	232
Region-year observations (β regression)	5,720	4,640
β -convergence, unconditional	−0.0288***	−0.0293***
Implied half-life (years)	23.7	23.3
σ (SD of log patent intensity), 2000	2.211	2.334
σ (SD of log patent intensity), 2020	1.464	1.539
Number of clubs selected by BIC	2	2
Advanced club (regions)	168	129
Lagging club (regions)	118	103
Ratio of club means, 2010–2020	11.9:1	14.6:1
Between-club share of total variance, 2000	67.7%	75.1%
Between-club share of total variance, 2020	67.1%	71.3%
Advanced-club persistence	96.9%	100.0%
Lagging-club persistence	89.7%	92.0%

Notes: The EU-only sample excludes Switzerland, Norway, and the United Kingdom. Both columns use the same specification and the same club-identification procedure as the main text. *** $p < 0.01$. Persistence rates compare the 2000–2009 and 2010–2020 period averages against a single fixed threshold (47.8 patents per million in the full sample, 48.8 in the EU-only sample). Figure A7 plots the four panels of the convergence illusion for the EU-only sample.

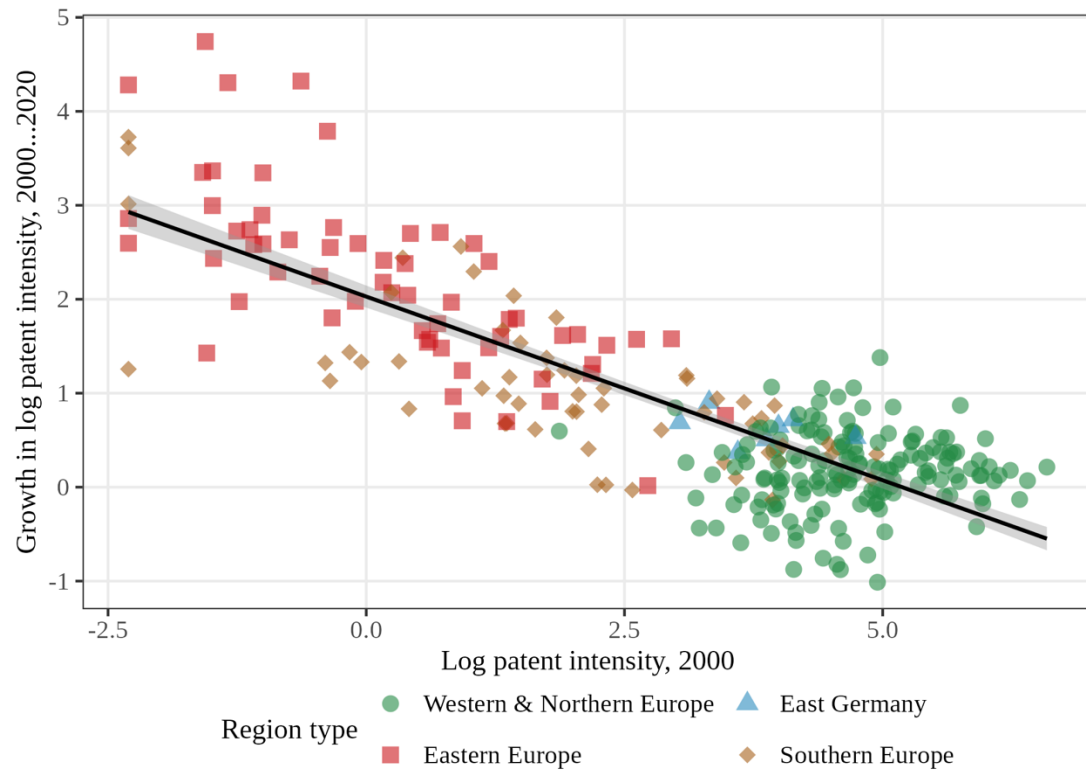


Figure A1: Beta-convergence in European regional innovation, 2000–2020

Note: Regression line based on unconditional Model 1 (OLS with year fixed effects). Each point represents one NUTS-2 region. Different symbols denote region types.

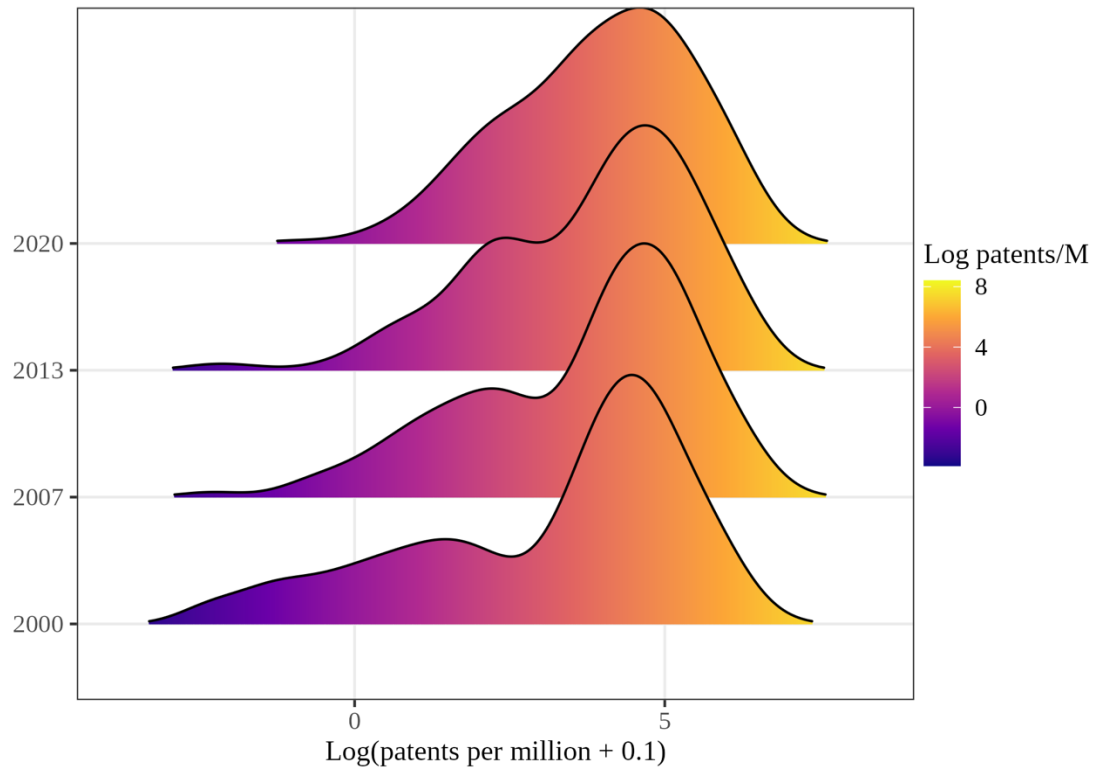


Figure A2: Distribution of regional innovation intensity. Bimodal structure persists across decades.

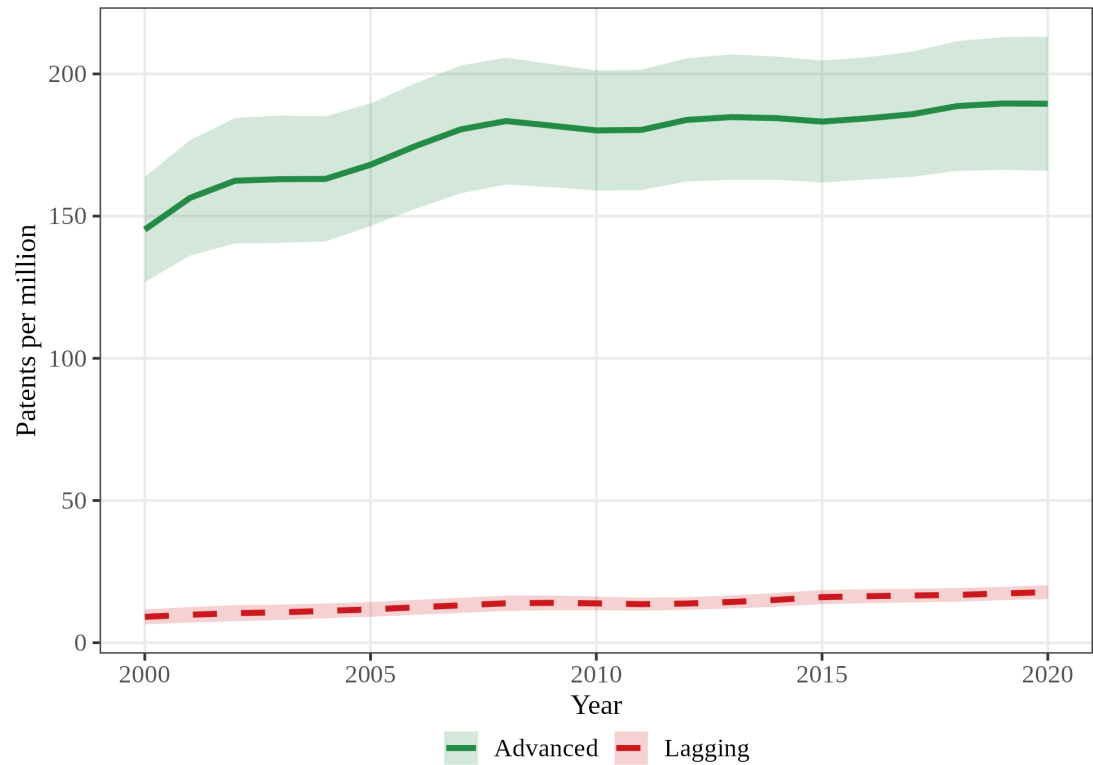


Figure A3: Mean patent intensity by club, 2000–2020. Shaded area: 95% confidence interval of the mean.

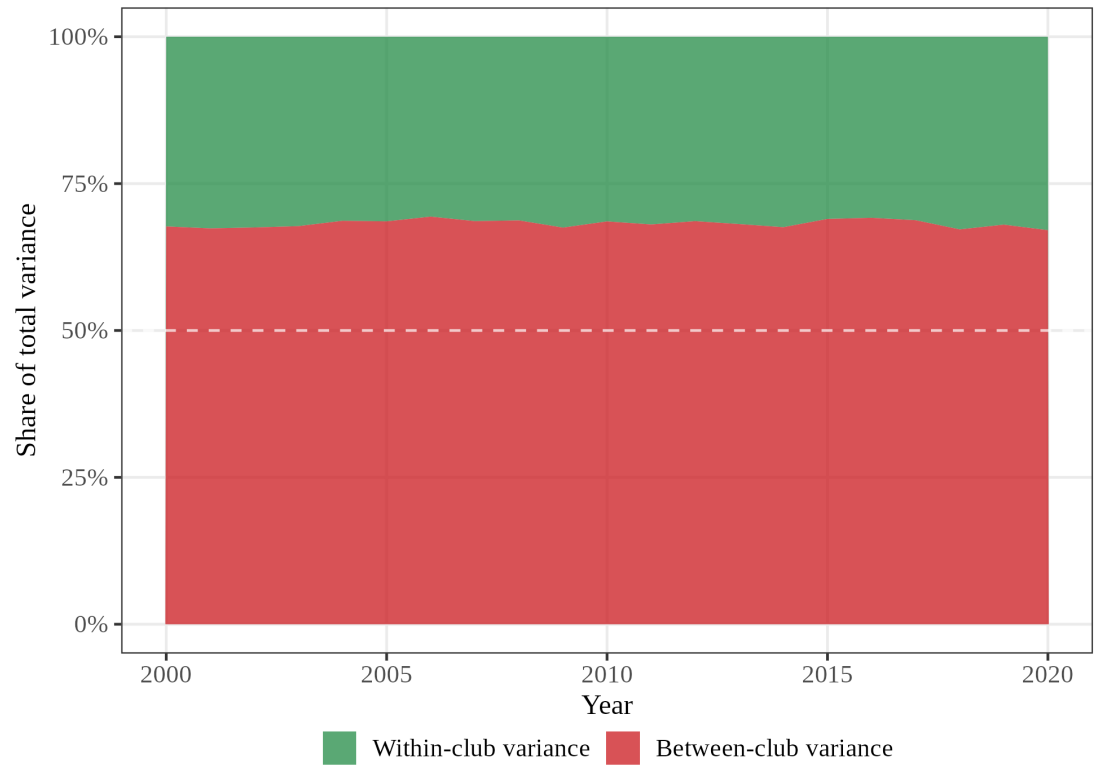


Figure A4: Variance decomposition – within vs between clubs. Share of total variance in the logarithm of patents per million

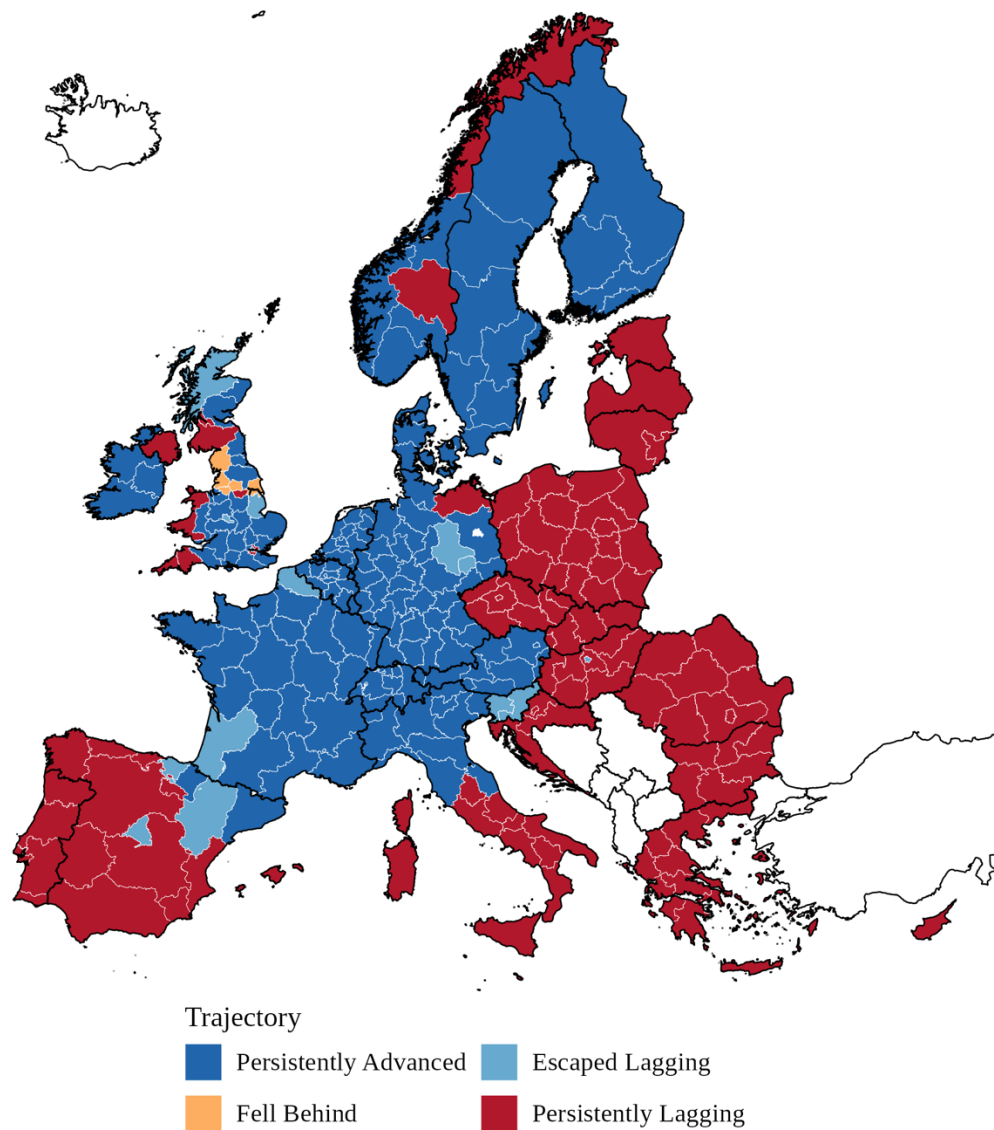


Figure A5: Regional innovation trajectories, 2000–2020.

Note: Trajectories based on club assignment in the early (2000–2009) and late (2010–2020) sub-periods against a single fixed threshold, the decision boundary of the Gaussian mixture model in Section 5.1 (47.8 patents per million).

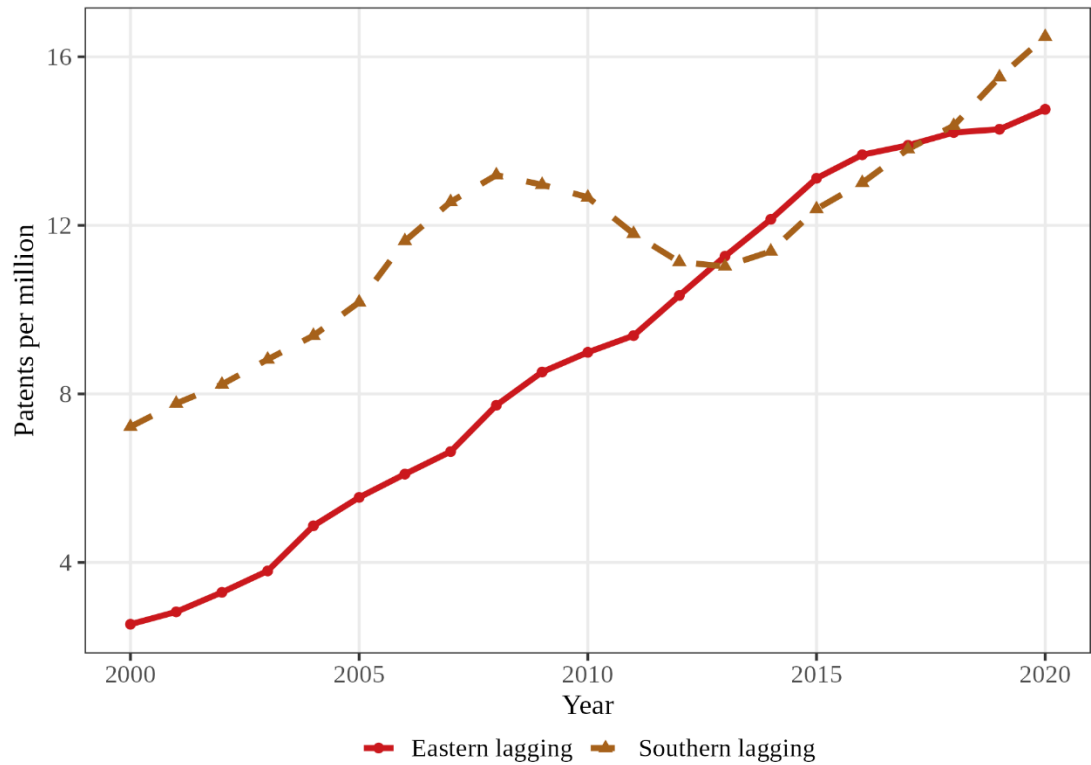


Figure A6: Trends in average patent intensity for the lagging eastern and southern regions. Convergence toward similarly low levels

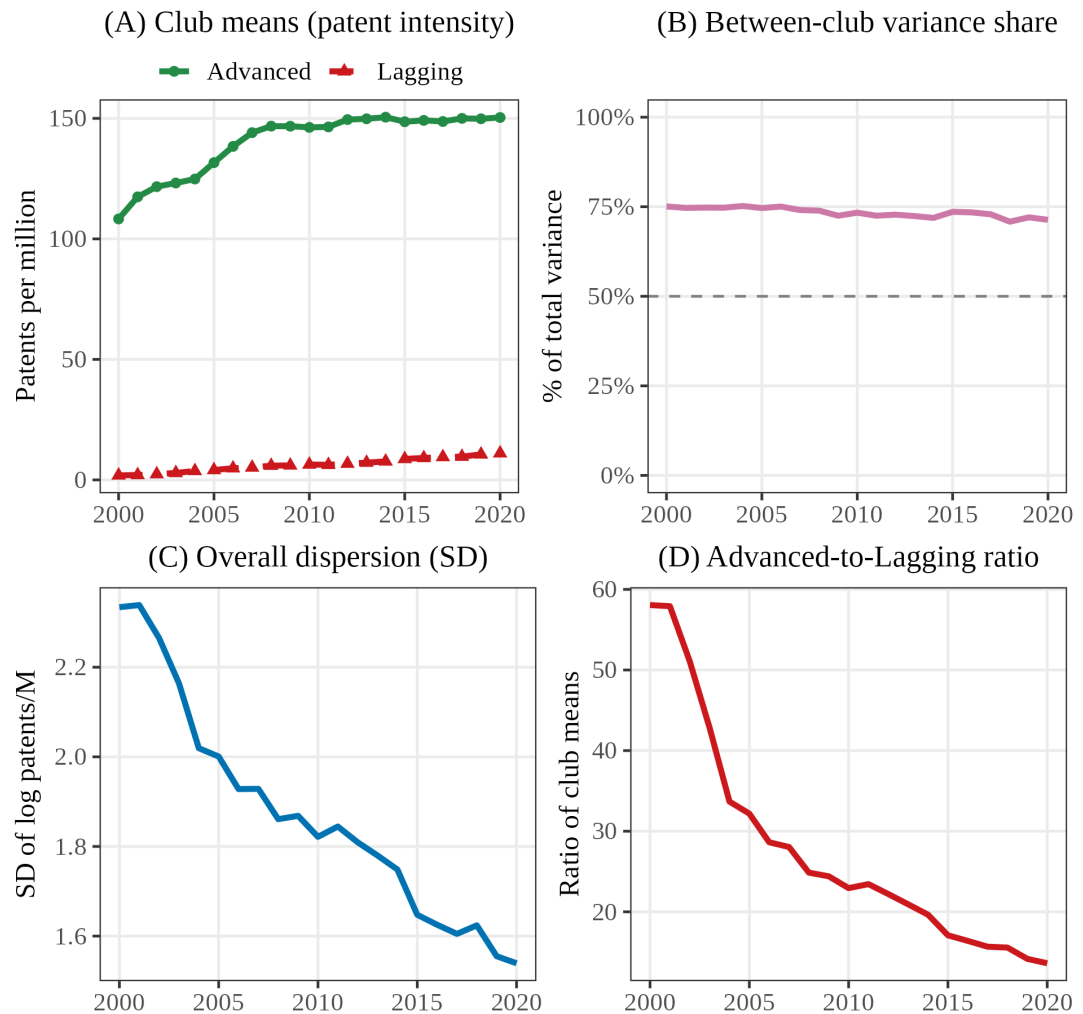


Figure A7. The convergence illusion, EU member states only

Notes: Panel A: club means in absolute patent intensity. Panel B: between-club share of total variance. Panel C: overall cross-regional dispersion. Panel D: ratio of Advanced to Lagging club means.

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