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The determinants and dynamics of regional convergence in the EU*

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Abstract

In this study, we employ the pairwise stochastic convergence approach to identify the pairs of NUTS2 regions for all 28 EU Member States that exhibit co-movement in their growth dynamics, over the period 1980-2018. We then use the observed stochastic convergence trajectories to assess the role of first nature geography, which is defined by variations in physical geography, locations and proximities, and second nature geography, corresponding to the economic interactions between partners, in causing economic growth convergence patterns. We find that western and northern parts of Europe have higher pairwise stochastic convergence (and lower intra-country convergence) rates than regions in East and Southeast Europe. Focusing on the converging NUTS2 regions, we find strong evidence that first and second nature geography drive cluster-like convergence dynamics. Regions with common locational characteristics (metropolitan, coastal, islands, and mountainous) tend to converge to each other, while they do not converge with dissimilar regions. Regardless of national borders, contiguity and accessibility are significant drivers of convergence. Congruence in sectoral specialisation results in divergence that could be driven by competing economic interests within the common market. The opposite holds for dissimilarities in specialisation, which could be explained by complementarity in the production process. Overall, we find strong evidence for stochastic club convergence at the top of the EU. In contrast, bottom regions with low market dynamism and poor economic development, do not converge to each other, and collectively lag significantly behind top European regions. Finally, we find evidence of EU Cohesion Fund payments facilitating the observed convergence dynamics across the EU, which highlights the importance of targeted regional policy interventions in reducing persistent structural regional disparities within the EU.

Keywords: Stochastic convergence, economic geography, pairwise approach, EU Member States, NUTS2 regions, EU Cohesion Fund.

JEL Codes: C51, O47, O52, R11.

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Introduction

The corpus of economic growth literature has been built on the neoclassical notion of beta-convergence, which pertains to low-income countries growing faster that high-income ones and thus eventually catching up with them in the long run. Although intuitive from a technological point of view (diminishing returns of capital), beta-convergence has been often criticised in the literature. These critiques focus on various conceptual issues such as the existence of a common steady-state (Durlauf, 1996) and the underlying notion of equilibrium (Fingleton & McCombie, 1999), the absence of distributional dynamics (Quah, 1993) and the lack of focus on local characteristics (Martin & Sunley, 1998). In general, most of the empirical studies in the economic growth literature tend to focus mainly on documenting convergence, rather than explaining the underlying factors that drive this economic phenomenon.

During the last decade, there has been a new stream of empirical studies that tries to connect the incidence of regional convergence to specific locational characteristics (e.g., Mello (2011), Heckelman (2013), Holmes et al. (2011); and Holmes et al. (2013)). The methodological basis for this type of empirical analyses is the notion of stochastic convergence, first introduced by Carlino & Mills (1993; 1996), more formally introduced by Bernard & Durlauf (1995), and later econometrically formalised by Pesaran (2007). Stochastic convergence occurs when pairs of regions experience co-moving income trajectories, or in other words the output gap between the pair of regions is a stationary process with constant mean. This type of convergence relaxes the neoclassical notion of convergence by allowing for absence of steady-state dynamics, non-convergence or, equivalently divergence, in cases of diminishing returns, and existence of endogenously driven club convergence. Out of the related studies, Arvanitopoulos et al. (2021) is the first study to develop a systematic methodological approach to robustly identify the incidence of pairwise stochastic convergence and use this information to thoroughly examine the first and second nature drivers of the observed convergence process. Using this methodology at the prefectural level of Greece, Arvanitopoulos et al. (2021) find significant evidence of cluster-like convergence.

So far, all related studies mainly focus on specific countries and more specifically they analyse convergence patterns between specific pairs of regions often called “benchmarks”. However, there are no studies that examine regional convergence dynamics at a larger geographical scale, and for all possible pairs of disaggregated regions within those geographical areas. This type of analysis can open the way for a more generalised identification of convergence drivers beyond national borders. The EU is an excellent example for such an analysis considering the increased variation in first and nature geography characteristics across and within Member States, and the existence of available historical data at a fine spatial unit. In addition, the existence of a common market across EU Member States lead to higher trade integration across regions, thus removing trade related regional specific institutional barriers. Hence potential concerns about institutional heterogeneity arising from uneven trade barriers across regions that could hinder the robustness of the proposed methodology are not observed. Although Próchniak & Witkowski (2015) examine stochastic convergence within the EU, they focus on the country level (NUTS1) and only test for convergence against the EU15 benchmark. Therefore, this is the first study to empirically examine the incidence of pairwise stochastic convergence across all 28 EU Member States (including the UK as our analysis is historical) for the longest period (1980-2018) and at the granular level of NUTS2 regional classification. We further use the observed pairwise convergence trajectories to identify the first and second nature drivers of this process. Our proposed methodological approach can be distinguished in two parts.

The first part of this analysis employs historical data at the NUTS2 level regions of the EU to test for the incidence of bilateral stochastic convergence during the past 40 year. We test all 37,950 bilateral pairs of NUTS2 regions within the EU for stochastic convergence. This allows us to identify the NUTS2 areas that experience common growth trajectories. We then examine the identified convergence patterns both at an aggregate level (EU), and in a more spatially disaggregated level, so that we thoroughly analyse the observed convergence patterns both within and across countries.

The second part of the analysis specifically focuses on the areas that exhibit stochastic convergence in their growth dynamics and examines the covariates that yield such positive test outcomes. To do that, we use covariates that control for the role of first nature (location, proximity, physical geography) and second nature geography (economic structure, agglomeration, economic potential) geography. We finally investigate the role European cohesion policy in facilitating the identified convergence trajectories across EU regions. This is particularly policy relevant as it can provide evidence on whether targeted policy intervention can help reduce regional disparities in the long-term period.

We find evidence that stochastic convergence within the EU follows a cluster-like pattern in terms of both geographical and economic determinants. From a geographical perspective western and northern parts of Europe have higher convergence rates than eastern and southeastern ones. We find strong evidence of club stochastic convergence among NUTS2 regions within the 15 EU Member States, which diverge from regions in countries that joined the EU after 1995. Focusing on locational characteristics, we find substantial evidence that first nature geography is significant driver of convergence. Regions sharing common locational characteristics such as being metropolitan, mountainous, islands, and coastal, converge, while they diverge from regions with dissimilar characteristics. Contiguity and accessibility are both significant determinants of convergence, regardless of national borders.

Focusing on second nature geography, we find evidence that congruence in sectoral specialisation results in non-convergence, probably driven by competition dynamics within the common market. The opposite holds for dissimilarity in sectoral specialisation. We find strong evidence of club convergence at the top of the EU. The bottom regions, characterised by poor economic development and low market dynamism, do not converge to each other while collectively lag significantly behind of the top European regions. Finally, we find significant evidence that pairs of regions with higher inputs of EU Cohesion Fund payments tend to converge, compared to regions that receive less Cohesion Fund payments. This finding supports the role of targeted regional policy interventions in facilitating convergence dynamics within the EU.

1. Data

We derive data on regional income, employment, and demographics from Cambridge Econometrics' European Regional Database (ERD). The primary source of the ERD dataset is Eurostat's REGIO database and secondary sources include the AMECO dataset (European Commission's Directorate General Economic and Financial Affairs). The ERD contains the longest time series on the abovementioned indicators that date back to 1980 for NUTS2 regions for the first 15 EU Member States[3], and from 1990 onwards for the countries that have joined the EU after 1995. More specifically, we use data on Gross Value Added and employment both at the aggregate level for NUTS2 regions, and at the sectoral level for agriculture, industry, and services sectors. Data on population report the number of people that reside at least one year within a NUTS2 region. Overall, we use regional historical data (when available) from 1980 till 2018. Although there is available data till 2020, we choose to use data till 2018, so that we avoid any potential structural breaks in our series due to the Covid pandemic and (to a lesser extent) the withdrawal of the United Kingdom from the EU.

As a proxy for human capital, we use data on the share of working age population that attended tertiary education. We derive regional data for tertiary education attainment for 2000 to 2018, at the NUTS2 level, from the QoG EU Regional dataset (Charron et al., 2020). Regarding historical data on EU Cohesion Fund (CF) payments for NUTS2 regions, we obtain data, spanning from 1994 to 2018, from the European Commission (DG Regional Policy).

[3] NUTS2 regions of East Germany are exception as there is available data from 1991 onwards (in contrast to rest of Germany).

More specifically, we use data on CF real expenditure payments modelled by the European Commission to reflect the actual (or “real”) expenditure rather than the reported cycle of payments of the European Commission to Member States. Given that data on EU CF payments are reported based on the 2013 NUTS2 boundaries, we use the EU NUTS converter – which is a web-based tool developed by the European Commission – to convert the boundaries from 2013 nomenclature to the corresponding 2016 boundaries.

We proxy for the role of first nature geography by controlling for specific locational and geographical characteristics, such as whether a region is metropolitan, urban, rural, mountainous, coastal, island, following the territorial typology developed and used by the Eurostat authority (European Commission (EU), 2018). More specifically, metropolitan areas are classified as those that represent agglomeration of at least 250 thousand inhabitants and are identified using the Urban Audit's Functional Urban Area (FUA). In case that there is an adjustment NUTS3 region that has more than 50% of the population living within this agglomeration, then this NUTS3 regions is also classified as metropolitan. NUTS3 areas are defined as urban areas if more than 80% of the population lives in clusters with population density of at least 300 inhabitants per square kilometre and minimum population 5000. In contrast, NUTS3 areas are defined as rural areas if at least 50 of the population lives in clusters with population density less than 300 inhabitants per square kilometre and maximum population 5000. Mountainous NUTS3 areas are considered those in which more than 50 % of their surface is covered by topographic mountain areas. Coastal NUTS3 regions are the regions with a sea border, and islands are those located on an island.

Regarding travel time and distance between EU NUTS2 regions within EU, we use a dataset developed by the EU Joint Research Centre (Persyn et al., 2020). The distance between NUTS2 regions is estimated by measuring the time and distance covered by a representative truck that uses optimal transport route to travel between regions (Persyn et al., 2020). We use this dataset to generate an accessibility measure for all EU NUTS2 areas that is constructed by taking the inverse of the sum of log-distances for each NUTS2 region from all other regions within the EU. Further details on the construction of all the corresponding first and second nature variables used in this study, can be found in the following section that outlines in detail the proposed methodological approach.

2. Empirical methodology

According to Pesaran (2007), the stochastic version of convergence is consistent with a more general form of the neoclassical endogenous growth model. To test for the existence of convergence, Pesaran (2007) employs a unit-root test on the output gap of a pair of economies ($g_{ij,t} = |y_{i,t} - y_{j,t}|$). Following Arvanitopoulos et al. (2021), we use complementary unit-root tests, beyond the traditional linear models (Augmented Dickey Fuller – ADF; GLS-detrended Dickey-Fuller – DFGLS), that are able to account for nonlinear (Kapetanios et al., 2003) and asymmetric nonlinear (Sollis, 2009) processes. We use the specified unit-root tests to examine for the incidence of stochastic convergence on all bilateral pairs of NUTS2 areas for the 28 EU member states[4]. Given we have 276 NUTS2 areas (based on 2016 EU boundaries), the total number of pairwise combinations is 37,950.[5] More specifically, our analysis builds on the econometric methodology developed and employed in Arvanitopoulos et al. (2021) which can be distinguished in the following two parts:

(i) we test for the incidence of stochastic convergence between all bilateral pairs of NUTS2 regions using linear, nonlinear, and asymmetric nonlinear unit-root tests,

(ii) we examine the role of first nature (or locational) characteristics and second nature (or economic geography) characteristics in driving the incidence of pairwise stochastic convergence across EU.

2.1. Testing for pairwise stochastic convergence

We start by testing the stationarity of the output gap g_{ijt} i.e., the difference in the real log per capita gross value added of regions *i* and *j*, employing the Augmented Dickey Fuller (ADF) unit-root test:

$$\Delta g_{ijt} = \alpha_{ij} + \beta_{ij} g_{ij,t-1} + \sum_{s=1}^{p_{ij}} \delta_{ijs} \Delta g_{ij,t-s} + \varepsilon_{ijt}, \tag{1}$$

To reject the null of non-stationarity, the *t*-statistic has to exceed the ADF critical value.[6] In the case that the null hypothesis is rejected, there is evidence of existence of output convergence between NUTS2 areas *i* and *j*. This means that there is a common long-run stochastic trend between the NUTS2 regions which by extension indicates the existence of common growth trajectories. We further implement the DF-GLS unit-root test. This unit-root applies as a prior step a GLS detrending before the ADF regression is estimated.

[4] Although UK has withdrawn from the EU on 31 December 2020, we incorporate it in our analysis as we use historical data spanning from 1980 (when available) to 2018.
[5] We use the formula N*(N-1)/2 to calculate the total number of pairwise combinations among NUTS2 regions within the 28 EU Member States.
[6] We estimate the ADF test with intercept and use the critical values -2.625, -2.971, and -3.689 at the 10%, 5%, and 1% significance levels, respectively. To determine the optimum lag number, we employ the Schwarz Information Criterion (SIC) with *p*-max=6.

Although appealing due their simplicity, the literature argues that the ADF and the DFGLS unit-root tests are characterised by reduced power in rejecting the null. In cases of highly persistent processes, Kapetanios et al. (2003) proves that an Exponential Smooth Transition Autoregressive process (ESTAR model) is more consistent under globally stationary conditions, and thus more powerful than the ADF unit-root test. The proposed nonlinear specification, known as the KSS unit-root test, can be specified as follows:

$$\Delta g_{ijt} = \sum_{s=1}^{p_{ij}} \rho_{ijs} \Delta g_{ij,t-s} + \delta g_{ijs,t-1}^{3} + \varepsilon_{ijt}, \quad (2)$$

where the null hypothesis is H_0*: δ=0*.[7] Finally, if one cannot *a priory* rule out the existence of asymmetries in the equilibrium adjustment process, then an additional extension of this nonlinear unit-root test is necessary. This is known in the literature as the asymmetric ESTAR (or AESTAR) unit-root test (Sollis, 2009) and can be specified as follows:

$$\Delta g_{ijt} = \sum_{s=1}^{p_{ij}} \rho_{ijs} \Delta g_{ij,t-s} + \varphi_1 g_{ijs,t-1}^{3} + \varphi_2 g_{ijs,t-1}^{4} + \eta_{ijt} \quad (3)$$

where the null hypothesis is H_0: φ_1=φ_2=0.[8] Given the AESTAR is a standard *F*-test, it allows the autoregressive parameters to take simultaneously proportional positive and negative deviations from the series' attractor. An additional function of this nonlinear test beyond testing for the presence of stationarity, it can identify whether nonlinearity is symmetric or asymmetric to positive and negative deviations of the output gap.

Finally, we compute the total fraction of unit-root rejections of the null hypothesis for each one of the four unit-root tests (ADF, DFGLS, KSS, and AESTAR) separately, for all pairwise EU NUTS2 pairs. In other words, we calculate the percentage of cases for which we obtain empirical evidence that supports the existence of long-term stochastic convergence trajectories among EU NUTS2 areas. We use this to assess the overall extent of cross-sectional stochastic convergence across EU areas.

[7] According to Kapetanios et al. (2003), there are three cases for raw, de-meaned and de-trended data. In this study, we present empirical findings only for the first case, being the most appropriate for our data. In similar fashion to the ADF and DF-GLS unit-root tests, we employ a KSS unit-root test with intercept and use the critical values -1.92, -2.22 and -2.82, at the 10%, 5% and 1% significance level, respectively. To determine the optimal lag length, we use the Schwarz Information Criterion (SIC) with *p*-max=6.

[8] In similar fashion to ADF, DGFLS and KSS unit-root tests, we employ the ESTAR test with intercept and use the critical values 4.16, 5.02, 6.97 for 10%, 5%, and 1% significance level, respectively (Cook, 2016). To determine the optimum lag number, we use the Schwarz Information Criterion (SIC) with *p*-max=6.

2.2. Drivers of stochastic convergence: the role of congruence and dissimilarity

Having identified the pairs of NUTS2 regions for which we have sufficient evidence that they stochastically converge, the next step involves analysing the underlying factors that drive this process. To do that we use the information derived from all four unit-root tests, as each provides us with alternative cross-section estimates of pairwise convergence. More specifically, we generate a dummy variable for each of the unit-root tests that takes the value of 1 if the unit-root test rejects the null hypothesis of non-convergence at the 10% significance level, otherwise is equal to 0. Thus, we transform the unit-root test statistics to binary form and use this as our dependent variable in a cross-sectional probit model estimated by maximum likelihood, that takes the following form:

$$Pr\left(C_{ij} = 1\right) = \Phi\left(\alpha + X_{ij}\beta + \kappa_i + \lambda_j + u_{ij}\right) \tag{4}$$

where $\boldsymbol{C}$ stands for the binary variable for convergence between NUTS2 i and j (with $i \neq j$); $\boldsymbol{\Phi}$ stands for the cumulative normal distribution function; $\boldsymbol{X}$ stands for the vector of pairwise locational characteristics, described more in depth below; $\boldsymbol{\kappa}$ and $\boldsymbol{\lambda}$ represent the "origin" and "destination" dummies (i.e., each pair of NUTS2 regions has one "origin" and one "destination" control); $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ stands for the model parameters; and finally $\boldsymbol{u}$ represents the vector of independent identically distributed (iid) random errors. Given the null of non-stationarity is rejected more strongly when the corresponding test statistic obtains a higher value in absolute terms, we use this feature to introduce importance weights in our probit model. To generate those importance weights, we use the absolute value of the corresponding unit-root test statistic, and thus a higher absolute value is given more weight than one that is closer to the critical value for rejecting the null hypothesis at the 10% statistical significance level. Below we focus more extensively on the first and second nature characteristics and discuss on the proxies used to control for their effect on pairwise stochastic convergence.

2.2.1. First nature geography

We control for various locational characteristics for which we are interested in examining whether they can explain historical convergence dynamics across NUTS2 regions in the EU. Given the information of these characteristics is provided at the more granular spatial level of NUTS3 regional classification, we construct the corresponding variables by computing the percentage of NUTS3 areas within each NUTS2 region that share the same characteristic. This means that a higher proxy value indicates that the corresponding locational characteristic (metropolitan, urban, rural, mountainous, coastal, islands) is more prevalent within a NUTS2 region, with maximum possible value being 1 and minimum 0. Given stochastic convergence is pairwise by nature as it indicates whether two regions converge (or diverge), we model our first nature variables in relational terms using two types of measures. The first captures the dissimilarity between two regions (computed as the absolute difference between two local values that are standardised by the range of values of these variables) and the second captures the congruence (computed as the product of two local values, similarly standardised).

To test for club convergence among the first 15 EU Member States (fourth EU enlargement), we construct a dummy variable that takes the value of 1 if the NUTS2 region is part of those Member States. Given this is a dichotomous variable, we construct the corresponding dissimilarity index by giving the value of 1 to pairs of regions only if one of the two regions is part of the first 15 EU Member States (otherwise 0). Similarly, we construct the corresponding congruence index by giving the value of 1 to pairs of regions that both satisfy the above-mentioned conditions (otherwise 0). Finally, we further examine on whether i) neighbourliness i.e., contiguity of administrative borders, and ii) being within the same country, are significant drivers of stochastic convergence. Both variables are by nature congruent, and thus we do not incorporate those two variables in the dissimilarity regression models.

2.2.2. Second nature geography

We move on to the set of variables that control for the role of second nature geography on the incidence of stochastic pairwise convergence. We examine three main groups of second nature characteristics i.e., economic geography, sectoral specialisation, and economic potential. Given the cross-sectional nature of our probit model (equation 4), we transform all time-varying variables outlined below to cross-section observations by taking their regional average over time. Then, we construct congruence and dissimilarity measures (all variables specified below are continuous in nature), similar to first nature variables.

We use as proxies for economic geography the accessibility index (already defined in Section 2), and population density which is defined as the total population per NUTS2 divided by the area coverage. For sectoral specialisation, we have constructed a Herfindahl-Hirschman index (HHI) that measures the level of specialisation diversity within a NUTS2 area. To do that we use GVA data for three economic sectors namely, agriculture, industry, and services. A lower HHI value is associated with higher sectoral diversification, and the opposite. We further focus on services, for which we proxy using the share of regional GVA on services sector compared to the total regional GVA. Regarding economic potential, we account for the role of education by controlling for the share of working population that attainted tertiary education. As a proxy for regional economic development, we use the regional GVA per capita. As an inverse proxy for labour dynamism, we use the regional inactivity rate that is defined as the share of population that is not part of the regional labour force. Finally, to control for the role of EU Cohesion Fund payments on driving the incidence of stochastic convergence, we use the regional share of EU Cohesion payments to the total regional GVA.

3. Results

3.1. Incidence of regional pairwise stochastic convergence

We start our empirical analysis by assessing the incidence of pairwise stochastic convergence across NUTS2 regions within the EU on the aggregate level. In total, we have 37,950 bilateral pairs of regions, for each one of which we examine whether the null hypothesis of non-stationarity (and thus non-convergence) is rejected. We perform this analysis to all four test-statistics outlined in Section 3 and compare the total fraction (or percentage) of rejections of the null hypothesis for each unit-root test at the 10%, 5%, and 1% statistical significance level. Focusing first on the 10% statistical significance level, we can observe in Table 1 that the ADF, DFGLS and AESTAR have very similar fractions of rejections, equal to 14%, 15% and 15%, respectively. KSS in the only unit-root test with substantially higher fraction of rejections compared to other three test.

Table 1. Total factions of rejections using pairwise stochastic convergence tests for EU NUTS2 areas

Unit-root test	Pairwise fraction of rejections of the null hypothesis		
	Fractions of rejections at		
	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$
ADF	0.14	0.09	0.04
DF-GLS	0.15	0.07	0.02
KSS	0.28	0.20	0.10
AESTAR	0.15	0.11	0.06

Notes: α indicates the statistical significance thresholds. The optimum lag number is determined using the SIC Criterion with $p_{max} = 6$.

Moving on to higher levels of statistical significance i.e., 5% and 1%, we can observe that the overall fraction of rejections drops proportionally for all unit-root tests, with KSS remaining the best performing test with the highest fraction of null hypothesis rejections equal to 20% at 5% significance level, and 10% at 1% significance level. This outcome is reasonable given the KSS test has increased power in rejecting the null compared to other three tests, especially in cases of persistent time series processes (Kapetanios et al., 2003). Overall, we find that 28% (or about 1 in 4) regions converges to another region at 10% significance level (focusing on the KSS test). It is important to look beyond the aggregate picture and analyse the incidence of convergence at a more granular spatial level. Given the KSS test has increased power in rejecting the null, we choose the KSS test statistics to map the fraction of rejections, and thus the rate of stochastic convergence, for every NUTS2 region.[9] Figure 1 allows us to visually observe and untangle the geography of stochastic convergence within Europe. NUTS2 regions with deeper blue colour are characterised by higher rates of pairwise convergence, while those with lighter blue colour by lower rates of pairwise convergence. To obtain a more spherical understanding of intra-country and inter-country stochastic convergence dynamics, we also present in Table 2 the average rate of pairwise convergence at the country level, and the rate of intra-country stochastic convergence (converge between regions within the same country). Thus, Figure 1 in conjunction to Table 2 allow us to draw a more detailed understanding of historical pairwise stochastic convergence dynamics across and within EU Member States. In general, Figure 1 shows that NUTS2 areas in western and northern parts of Europe are the ones historically experiencing the highest rates of pairwise stochastic convergence. In contrast, east and southeast NUTS2 areas are the ones with the lowest rates of pairwise stochastic convergence in Europe.

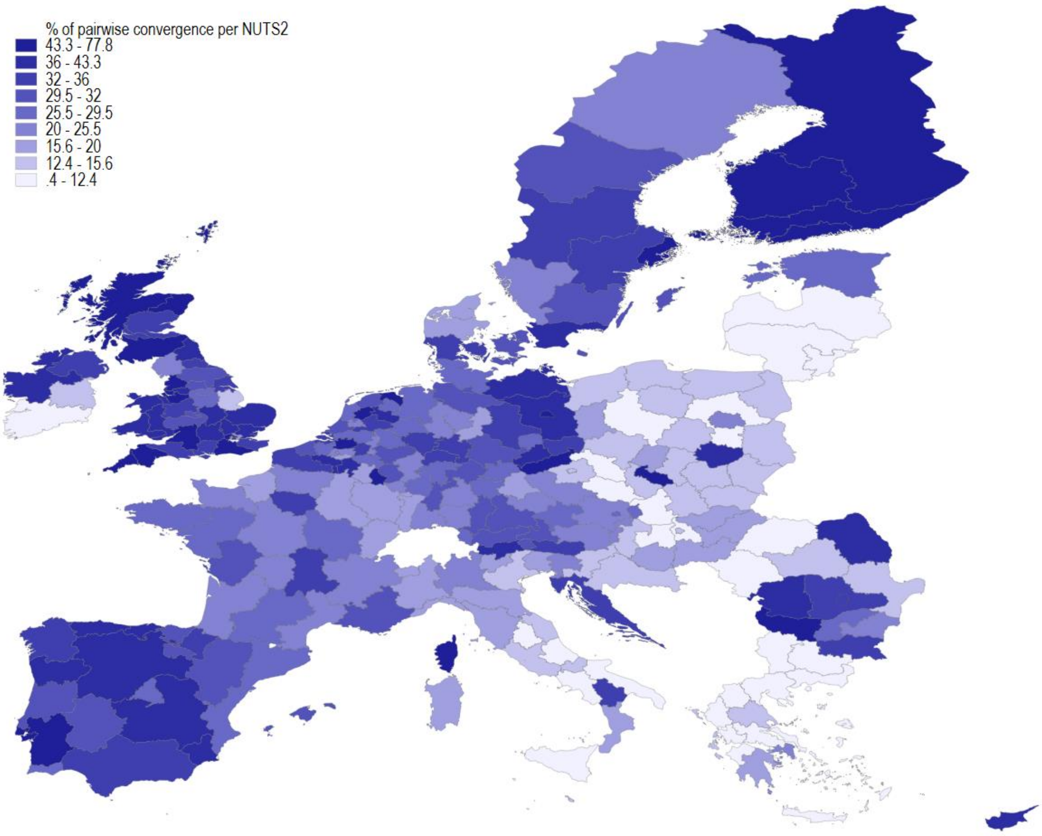
We are interested in analysing separately the convergence rate for all EU countries, as this can help us understand better the underlying patterns that drive the incidence of stochastic convergence. To do that, we start our analysis focusing on the countries with the highest rates of regional pairwise convergence and then gradually moving on, in descending order of convergence rates, to the worst performing ones. The top three performing countries are Luxemburg (69% convergence rate), Finland (60%), Portugal (51%). Within Portugal, areas such Alendejo (PT18) and Norte (PT11) are among the highest converging NUTS2 regions in Europe. Both Finland and Portugal have very low shares of intra-country convergence, equal to 2% in both cases. One could argue that larger countries with a higher number of NUTS2 areas might naturally tend to have larger intra-country rate of convergence than smaller ones (see for example Finland or Portugal). However, we find that this is not the case, as for example the country with the highest rate of intra-country convergence is Greece (similar size

[9] Similarly, we have produced the corresponding Figure 1 and Table 2 for the rate of convergence estimated using the ADF, DFGL, and Sollis unit-root tests. Results across unit-root tests are very similar for the majority of NUTS2 regions, and thus we refrain from presenting these for brevity purposes.

to Portugal) while larger countries such as France are characterised by only 8% of intra-country convergence.[10]

Cyprus and United Kingdom have 42% and 39% pairwise convergence rates, respectively. Among the best performing countries on pairwise convergence, the UK is the only country to also have a substantially high share of intra-country convergence (22%), being the second largest only after Greece (25%). This means that approximately about 1 in 5 converging NUTS2 areas in the UK converges to another NUTS2 region within the same country. Focusing more on the British Isles, the overall picture is more complicated as there is large variation in the pairwise convergence rates across the country. For example, one can observe in Figure 1 that Lancashire (UKF3) experiences a very low rate of convergence while the neighbouring region of East Anglia (UKH1) is among the highest converging areas within the country.

Figure 1. Share of pairwise stochastic convergence per NUT2 area across the EU from 1980-2018



Notes: NUTS2 regions with deeper blue colour are characterised by higher rates of pairwise stochastic convergence, while those with lighter blue colour by lower rates of pairwise stochastic convergence.

[10] Small EU Member States such as Cyprus, Estonia, Latvia, Luxembourg and Malta are only characterised by one NUTS2 region. In this case it is not possible to infer outcomes about intra-country convergence.

Sweden and Netherlands perform similarly well in terms of pairwise convergence rates (36% and 34%, respectively), while both have very low intra-country convergence rate (5%). Spain and Germany are next with 32% and 30% of average pairwise convergence rates, respectively, and intra-country convergence rates equal to 12% and 15%, respectively. Focusing specifically on Spain (Figure 1), we observe that areas such as Castilla-La Mancha (ES42), Cantabria (ES13), Principado de Asturias (ES12), and Región de Murcia (ES62), are the areas with the highest rates of pairwise convergence within the country. NUTS2 regions that incorporate the major metropolitan areas within Spain, such as Comunidad de Madrid (ES30), Cataluña (ES51), and País Vasco (ES21), have relatively lower rates of convergence compared to other Spanish NUTS2 areas. Moving on to Germany, we observe in Figure 1 that eastern NUTS2 areas within the country, such as Brandenburg (DE40), Berlin (DE30), and Mecklenburg-Vorpommern (DE80), tend to have higher rates of pairwise convergence compared to their western counterparts.

The rest of the western and northern EU Member States complete the picture of high pairwise convergence rates (i.e., Belgium 29%, Austria 28%, Denmark 26%) with only exceptions Bulgaria and Estonia that score 29% and 27% of convergence rates, respectively. Within Bulgaria there is large variation in convergence rates as northern regions – these include the major metropolitan areas and are contiguous to Romania – experience significantly higher pairwise convergence rates than those in the south of the country that are contiguous to Greece. France is the largest western EU country with the lowest share of pairwise convergence rate (26%). Within France, one can observe in Figure 1 that NUTS2 areas in the north and east of the country (those contiguous to Belgium, Luxemburg, and Germany) have lower rates of convergence, compared to southern and western NUTS2 areas. The only exceptions in the north of France are the regions of Nord-Pas de Calais (FRE1) and Ile-de-France (FR10) which experience higher convergence rates. The former is an important trade hub, and the latter incorporates the largest metropolitan area in France.

Moving on to East and Southeast Europe, convergence rates are significantly lower than the ones discussed so far. Croatia and Czech Republic score 26% and 25% on average pairwise convergence rates. Within Czech Republic, we can observe in Figure 1 that the highest converging NUTS2 regions are the ones contiguous to neighbouring countries such as Severozápad (CZ04) and Jihozápad (CZ03) both neighbouring Germany, and Moravskoslezsko (CZ08) neighbouring Poland. Romania scores 20% of pairwise convergence rate, mainly driven by the highly performing southern part of the country that incorporates the metropolitan region of Bucharest. Slovenia scores 19% pairwise convergence, a value very similar to that for Ireland (18%) which is the only western EU country to score so low on average rate of pairwise convergence. Italy scores 17% both for pairwise convergence rate, and for intra-country convergence rate. Focusing more on Italy, we can observe in Figure 1 that the southern NUTS2 regions of the country experience very low pairwise rate of convergence, with only exceptions the regions of Basilicata (ITF5) and Calabria (ITF5). In contrast, the northern regions of Italy experience substantially higher rates of convergence, with the regions of Toscana (ITI1) and Emilia-Romagna (ITH5) being the southernmost most highly performing regions in the north of the country.

Table 2. Country average stochastic convergence rate across EU and within country

Country code	Country	Number of NUT2 areas per country	Average pairwise (across EU) stochastic convergence rate per country	Average intra-country stochastic convergence rate per country
AT	Austria	9	0.28	0.04
BE	Belgium	11	0.29	0.04
BG	Bulgaria	6	0.29	0.02
CY	Cyprus	1	0.42	NA
CZ	Czech Republic	8	0.25	0.06
DE	Germany	38	0.30	0.15
DK	Denmark	5	0.26	0.01^
EE	Estonia	1	0.27	NA
EL	Greece	13	0.10^	0.25~
ES	Spain	19	0.32	0.12
FI	Finland	5	0.60~	0.02
FR	France	22	0.26	0.08
HR	Croatia	2	0.26	0.00^
HU	Hungary	8	0.16	0.13
IE	Ireland	3	0.18	0.00^
IT	Italy	21	0.17	0.17~
LT	Lithuania	2	0.07^	0.05
LU	Luxembourg	1	0.69~	NA
LV	Latvia	1	0.10^	NA
MT	Malta	1	0.15	NA
NL	Netherlands	12	0.34	0.05
PL	Poland	17	0.16	0.18~
PT	Portugal	7	0.51~	0.02
RO	Romania	8	0.20	0.01^
SE	Sweden	8	0.36	0.05
SI	Slovenia	2	0.19	0.02
SK	Slovakia	4	0.16	0.04
UK	United Kingdom	41	0.39	0.22~

Notes: Although UK has withdrawn from the EU on 31 December 2020, we incorporate it in our analysis as we use historical data spanning from 1980 (when available) to 2018. "~" Indicates that three top shares of average pairwise stochastic convergence across EU and within country, while "^"indicates the three bottom ones.

Slovakia, Poland, and Hungary share the same share of pairwise convergence (16%), while Poland and Hungary also have relatively high rates of intra-country convergence (18% and 13%, respectively). Within Poland, only exceptions in the overall low performance are the NUTS2 regions of Opolskie (PL52) that is contiguous to Czech Republic, Lubuskie (PL43) and Zachodniopomorskie (PL42) that are contiguous to Germany, and Pomorskie (PL63) and Warszawski stołeczny (PL61) that both incorporate significant metropolitan clusters (the former also being coastal). Finally, the worst performing countries on average pairwise stochastic convergence rates are Malta (15%), Greece (10%), Latvia (10%), and Lithuania (7%). An interesting observation is that Greece is among the worst performing countries regarding average convergence rate (10%) and the best performing country regarding intra-country convergence rate in Europe (25%). The latter effectively means that 1 in 4 converging regions in Greece converges to another NUTS2 area within the country.

3.2. First nature geography and pairwise stochastic convergence

Focusing on first nature geography, Table 3 presents the results on the effect of locational characteristics on the incidence of convergence drawing on two types of comparison. The first four models specify on the dissimilarity of those characteristics and their effect on pairwise convergence, while the next four models specify on the congruence of the location characteristics for each pair of regions. In both cases, we use alternative dependent variables based on the four different types of test-statistics used in this analysis (i.e., ADF, DF-GLS, KSS, and AESTAR). We get highly consistent results across all test-statistics in Table 3, which supports the robustness of our empirical findings (presented below).

In general, we find strong and consistent evidence of club formation across EU NUTS2 areas that share similar locational characteristics such as being metropolitan, coastal, and mountainous. Starting with metropolitan areas, we find statistically significant evidence in three model specifications (ADF, DFGLS, and KSS) that congruence results in convergence, while exactly the opposite result holds for dissimilarity. Similarly, mountainous and coastal areas strongly converge to congruent regions, while they diverge from areas with different locational characteristics (dissimilarity). Islands regions also converge to congruent regions, and diverge from dissimilar, although we find only statistically significant results for this locational characteristic only in the ADF model specification (both for congruence and dissimilarity models). Results for urban and rural are mixed. Focusing on dissimilarity models, we observe in Table 3 that urban areas converge to non-urban regions in the DFGLS model, while they diverge in the AESTAR model. In contrast, congruence in the degree of urbanity results in divergence (DFGLS test). Similarly, dissimilarity in rural areas results in divergence (AESTAR test), a result that also holds for congruence (DFGLS test).

Table 3. The role of locational characteristics on the incidence of pairwise stochastic convergence in the EU

	Dissimilarity				**Congruence**			
	ADF	**DF-GLS**	**KSS**	**AESTAR**	**ADF**	**DF-GLS**	**KSS**	**AESTAR**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Metropolitan	-0.017**	-0.042***	-0.037***	0.00013	0.055***	0.110***	0.086***	-0.008
	(0.008)	(0.008)	(0.008)	(0.009)	(0.017)	(0.018)	(0.016)	(0.019)
Urban	-0.008	0.038***	-0.006	-0.014*	0.0014	-0.074***	0.0069	0.014
	(0.007)	(0.008)	(0.007)	(0.008)	(0.0128)	(0.0143)	(0.0123)	(0.014)
Rural	-0.0074	-0.0017	-0.011	-0.027***	0.0143	-0.034**	0.015	0.031*
	(0.009)	(0.009)	(0.008)	(0.009)	(0.015)	(0.015)	(0.014)	(0.016)
Coastal	-0.044***	-0.053***	-0.038***	-0.047***	0.076***	0.088***	0.061***	0.067***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.01)	(0.01)	(0.01)	(0.011)
Islands	-0.048***	-0.029	-0.013	-0.017	0.091***	0.044	0.024	0.040
	(0.0185)	(0.0185)	(0.0186)	(0.022)	(0.035)	(0.035)	(0.035)	(0.041)
Mountainous	-0.039***	-0.046***	-0.056***	-0.043***	0.056***	0.042***	0.067***	0.052***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.012)	(0.013)	(0.012)	(0.014)
EU 15	-0.223***	-0.231***	-0.316***	-0.182***	0.434***	0.439***	0.614***	0.334***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.013)	(0.013)	(0.012)	(0.014)
Contiguous					0.036**	0.017	0.022	0.029*
					(0.015)	(0.016)	(0.015)	(0.016)
Same country					0.033***	0.094***	0.064***	0.088***
					(0.007)	(0.008)	(0.007)	(0.008)
Pseudo-R^2	0.27	0.15	0.21	0.27	0.27	0.15	0.21	0.27
Observations	74,802	75,900	75,900	75,350	74,802	75,900	75,900	75,350

Notes: This table shows the marginal effects from weighted maximum likelihood probit estimates. Dummies for 'origin' and 'destination' are introduced in the model to control for fixed effects. Dissimilarity and congruence have been defined in Section 2. Robust standard errors reported in parentheses. *, ** and *** indicate statistical significance level at the 10%, 5% and 1% level, respectively.

We further test for club convergence between NUTS2 areas located within the first 15 EU Member States, compared to those entered the EU after 1995 (fourth EU enlargement). We find strong and consistent evidence that areas within the first 15 EU Member States converge to each other, while they diverge from regions located in the rest of the EU countries. We find strong and consistent evidence of convergence between pairs of regions located within the same country. Similarly, we find that contiguous NUTS2 regions tend to converge. Given we already control for the same country effect, the contiguity variable effectively controls for converging regions that are neighbours but are not located within the same country. To test whether this holds, we re-estimate all models without the same country variable, for which we indeed find that contiguity coefficient becomes statistically significant across all models (compared to only the ADF and AESTER models in Table 3). Therefore, we are confident that contiguity is a significant driver of stochastic convergence within the EU, regardless of national administrative borders.

3.3. Second nature geography and pairwise stochastic convergence

Having identified the first nature characteristics that can influence the incidence of pairwise convergence across NUTS2 regions, we move on to second nature geography. We examine the effect on incidence of convergence of characteristics associated to economic geography (accessibility, density), sectoral structure (specialisation, services share), and economic potential (education, development, inactivity rate, and Cohesion Fund payments). Once again, we construct dissimilarity and congruence indices for our independent variables and estimate the probit model (specified in Equation 5) using all four test-statistics as alternative dependent variables.

We start our analysis with the economic geography variables (see Table 4). We find strong and consistent evidence across all models that congruence in accessibility levels results in stochastic convergence, while dissimilarity results in divergence. The opposite pattern can be observed for population density. Regions with higher population density tend to converge to those with lower density, while those with congruent degrees of population density diverge. Therefore, our results indicates that although geographical accessibility facilitates convergence, areas with higher density tend to diverge, a result that probably reflect our previous finding that areas with higher share of urban clusters tend to diverge from each other.

Moving on to sectoral structure, we find strong and consistent evidence for the effect of sectoral specialisation on convergence dynamics. In all congruent models, sectoral specialisation results to divergence, while the opposite holds for dissimilarity models. This essentially means that regions with congruent sectoral specialisation, and probably competing economic interests within the common EU market, tend to diverge from each other. In contrast, regions with dissimilar specialisation, and most probably producing complementary goods and/or services, tend to converge to each other. Focusing specifically on the effect of specialisation on the services sector, we get statistically significant results in two congruent models (ADF and KSS) and one dissimilarity model (KSS). Similar to the overall sectoral specialisation results, congruence in services specialisation leads to divergence, that could be explained by competition dynamics, while the opposite result holds for congruence.

The effect of economic potential on stochastic convergence is proxied by the third set of variables in Table 4. Starting with university education, areas with dissimilar human capital diverge as indicated by the statistically significant and negative coefficient in three dissimilarity models (ADF, DFGLS, and KSS). Congruence in university education does not seem to play a statistically significant role in stochastic convergence (weak evidence only for the AESTAR test). The coefficient of development in all congruent models is positive and statistically significant, while exactly the opposite result holds for dissimilarity models. This indicates strong and consistent evidence of club-convergence at the top, as regions with congruent degree of development tend to converge to each other. Regions with dissimilar level of development diverge. Thus, we do not find any supportive evidence of beta-convergence dynamics across the EU. We further use the inactivity rate as an inverse proxy of labour market dynamism. Results indicate that regions with low market dynamism tend to diverge from each while a clear conclusion for dissimilar regions cannot be drawn. Finally, we find strong and consistent evidence that increased shares of EU Cohesion Fund payments (compared to regional GVA) boost convergence dynamics across the EU. The opposite result holds for pairs of regions with lower inputs of EU Cohesion Fund payments, which tend to diverge. Thus, our results support the argument that EU Cohesion Fund payments have historically facilitated the formation of convergence dynamics across the EU.

Table 4. The role of second-nature geography on the incidence of pairwise stochastic convergence in the EU

	Dissimilarity				**Congruence**			
	ADF	**DFGLS**	**KSS**	**AESTER**	**ADF**	**DFGLS**	**KSS**	**AESTER**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Economic geography								
Accessibility	-0.121***	-0.110***	-0.030**	-0.128***	0.379***	0.717***	0.029	0.305***
	(0.013)	(0.013)	(0.012)	(0.015)	(0.079)	(0.093)	(0.081)	(0.093)
Density	0.170***	0.412***	0.083	0.068	-0.293***	-0.629***	-0.187*	-0.176
	(0.057)	(0.085)	(0.055)	(0.06)	(0.105)	(0.132)	(0.101)	(0.116)
Sectoral structure								
Sectoral specialisation	0.0909***	0.112***	0.164***	0.147***	-0.937***	-0.657***	-1.214***	-1.041***
	(0.029)	(0.031)	(0.028)	(0.032)	(0.194)	(0.187)	(0.208)	(0.199)
Services	-0.0024	0.0173	0.034*	-0.002	-0.303**	-0.081	-0.286**	-0.243
	(0.02)	(0.021)	(0.019)	(0.022)	(0.151)	(0.135)	(0.138)	(0.148)
Economic potential								
Tertiary education	-0.076***	-0.108***	-0.071***	-0.034	-0.041	0.005	-0.013	-0.165*
	(0.021)	(0.023)	(0.020)	(0.024)	(0.082)	(0.094)	(0.081)	(0.089)
Development	-0.507***	-0.430***	-0.821***	-0.395***	2.598***	1.883***	3.638***	1.977***
	(0.026)	(0.028)	(0.025)	(0.029)	(0.142)	(0.138)	(0.160)	(0.145)
Inactivity rate	-0.026*	-0.072***	0.007	0.038**	-0.058***	-0.091***	-0.034**	0.0109
	(0.0150)	(0.0160)	(0.0143)	(0.017)	(0.015)	(0.016)	(0.014)	(0.016)
Cohesion Fund payments	-0.065***	-0.147***	-0.058***	-0.085***	0.318***	0.397***	0.365***	0.319***
	(0.020)	(0.020)	(0.019)	(0.023)	(0.031)	(0.030)	(0.030)	(0.034)
Pseudo R-squared	0.26	0.14	0.19	0.26	0.26	0.14	0.19	0.27
Observations	74,802	75,900	75,900	75,350	74,256	75,350	75,350	74,802

Notes: This table shows the marginal effects from weighted maximum likelihood probit estimates. Dummies for 'origin' and 'destination' are introduced in all model specifications to control for fixed effects. Dissimilarity and congruence have been defined in the text. Robust standard errors reported in parentheses. *, ** and *** indicate statistical significance level at the 10%, 5% and 1% level, respectively

4. Discussion

This study examines the incidence of stochastic convergence within the EU and uses the observed convergence trajectories to identify the determinants of first and second nature geography that drive this process. The proposed methodology is based on the notion of stochastic convergence. More specifically, our analysis builds on the empirical methodology developed and employed in Arvanitopoulos et al. (2021). This is the first study to examine the determinants and dynamics of regional pairwise stochastic convergence for all EU Member States (including the UK), for the longest time period (1980-2018), and at a fine granular spatial level (NUTS2). Overall, we test for convergence all 37,950 pairs of NUTS2 regions within the EU.

In general, we find that countries with higher average rate of pairwise stochastic convergence tend to have lower shares of intra-country pairwise convergence. The opposite result holds for countries with low average stochastic convergence rates that tend to have higher shares of intra-country convergence. This result highlights that open economies, characterised by increased trade exposure and reliance on external financing sources, tend to have higher convergence rates than closed economies. Least convergent and more closed economies are those in the Southeast Europe (e.g., Greece and south Italy) and the East of Europe (e.g., Poland). In contrast, western and northern parts of Europe experience higher rates of pairwise stochastic convergence (with only exception Ireland). This finding is further supported by the fact that we find strong evidence of club convergence among the oldest EU Member States, most of them located in the northern and western parts of Europe. Only exceptions are Greece and southern parts of Italy that tend to follow similar stochastic convergence patterns to those found for eastern European regions.

Secondly, we identify the first and second nature characteristics that drive the observed pairwise stochastic convergence patterns across the EU. Starting with first nature geography, our results clearly indicate that stochastic convergence within the EU follows a cluster-like pattern. We find strong evidence that metropolitan, coastal, mountainous, and islands areas tend to converge to areas with congruent geographical characteristics, while diverging from dissimilar regions. Contiguity is a key driver of convergence, regardless of national administrative borders. To better understand the observed dynamics, we can use Poland as a useful example, given it has overall very low stochastic convergence rates, with only a handful of NUTS2 regions breaking this trend. The highly stochastically convergent regions within Poland are those neighbouring Germany and Czech Republic, while the only exceptions of highly convergent regions within the centre of the country are the two main metropolitan areas, one of which is also coastal. Diving deeper on the underlying dynamics that drive the observed stochastic convergence patterns, we find strong evidence that geographical accessibility is a key component for shaping common convergence trajectories across the EU. On the other hand, congruence in the degree of agglomeration tends to be a key divergence characteristic.

Beyond locational characteristics, we use second nature geography to understand how economic geography drives the convergence dynamics within the EU. Focusing on market characteristics, we find strong evidence that congruence in sectoral specialisation results in divergence, while the opposite result holds for dissimilarity in specialisation. This finding illustrates the significant role of competition dynamics within the common market regarding convergence trajectories. Areas with competing sectors tend to diverge while complementarity in sectoral specialisation generates convergence dynamics between regions. Moving on to economic potential, we find strong evidence of club convergence at the top of the EU. Similarly, congruence in human capital at the top is not relevant for stochastic convergence, while areas with dissimilarities in human capital diverge. The lack of any significant beta-convergence dynamics is rather striking, as our findings indicate that low performing regions diverge from the highly performing ones. In other words, bottom regions are systematically left behind in the EU growth process. This may be attributed to the slowing down of convergence which is observed after the economic and financial crisis which started in 2008 (Monfort, 2020). In addition, we find evidence of non-convergence dynamics among areas characterised by low market dynamism, and by extension low activity rates. Therefore, regions at the bottom – characterised by low market dynamism and poor economic development – do not converge to each other, and collectively lag significantly behind of the top European regions which converge together at the top.

Thus, low performing regions are left out of the EU growth dynamics, and given they lack the necessary economic potential to step out of this divergence trap, it seems highly unlikely that they will be able to converge to top regions without the appropriate exogenous financial support. Indeed, we do find strong evidence that regions receiving higher inputs of Cohesion Fund (CF) payments tend to converge, while the opposite result holds for regions with which receive less CF payments. This finding highlights the historical importance of CF payments in facilitating stochastic convergence dynamics within the EU. Given that recipients of CF payments are regions with the lowest 10% regional income per capita within the EU, it becomes obvious that these payments can become a helpline for regions with poor economic development and low market dynamism, as these payments can assist their efforts in stepping out of long-term divergence dynamics. Thus, this study provides supportive evidence on the role of targeted regional policy interventions in reducing long-term regional disparities within the EU.

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