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Growing Differently: European Integration and Regional Cohesion

Jan David Weber and Jan Schulz

Abstract: We document two novel stylized facts on European integration and cohesion. First, we show that the interregional income distribution, measured as GDP per capita at the NUTS-3 (Nomenclature des unités territoriales statistiques) level, is bimodal for all considered years. Second, we demonstrate that this mixture of two log-normal distributions provides an excellent fit for this interregional distribution in all considered years. We put forward two meso-level interpretations of these stylized facts, based on heterodox growth theory: The log-normality of the individual clusters hints at a cumulative growth process, where growth is strongly path-dependent. However, the bimodality in the income distributions also implies two separate growth mechanisms. We show that the high-variance log-normal distribution governs the dynamics at both tails of the income distribution, which might be interpreted as the core and periphery, and the low-variance variant the bulk of the distribution, thus interpretable as a semi-periphery. Based on these theoretical mechanisms, we propose a taxonomy of European regions that is not based on arbitrary GDP thresholds.

Keywords: inequality, Europe, maximum entropy, Geometric Brownian Motion, core, periphery, resilience

JEL Classification Codes: O18, R11, C51, F15

In 1999, eleven member states of the European Union fixed their exchange rates, a first step towards the introduction of the first euro bills in 2002 (Raymond 1999). To implement a common monetary policy within a currency area, roughly uniform development of these regions is necessary for the policy to be adequate for all regions. The (newer) theory of optimum currency areas (OCAs), pioneered by Paul de Grauwe (2018), has emphasized the role of shock absorption capabilities that allow for homogeneous development even in the presence of asymmetric shocks. By contrast, regional clustering and divergent regional development paths would cast doubt on the eurozone as an optimum currency area (OCA). Indeed, there is now widespread scholarly agreement that the eurozone cannot be (fully) considered to be an OCA (Jager and Hafner 2013; Krugman 2013). Empirical studies on regional inequality and OCAs have typically focused on correlational patterns between

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business cycles at the country level. Our focus is more granular and emphasizes the role of distributional regularities at the NUTS-3 level (NUTS refers to “Nomenclature des unités territoriales statistiques”). We document that the regional income distribution (measured as GDP per capita) is bimodal in its bulk with a long upper tail. The short time-series length for which we have complete data on European regions prevents the use of any of the standard econometric techniques to examine growth processes. Instead, we propose a plausible data-generative process based on the observable interregional income distribution to shed light on the time development of European regions that we cannot directly observe (Schulz and Milakovic 2023).

We show that a plausible process generating this distributional pattern is multiplicative growth with two distinct volatility regimes. This type of process of multiplicative growth features heavily in heterodox growth theory, depending on the relevant school of thought as “circular cumulative causation,” “hysteresis,” or the “rich-get-richer phenomenon.” If we interpret realized volatility as a proxy for shock absorption capabilities, this finding highlights the role of regional resilience and multiplicative path-dependent growth. We thus provide a readily usable way to measure shock absorption capabilities that are also not directly observable. In this sense, European regions appear to be far from the benchmark of constituting an optimum currency area, and regional convergence of fiscal policies might be necessary to homogenize shock absorption capabilities across regions and facilitate cohesion. Our major contribution based on this finding is a taxonomy of regions based on the characteristics of the interregional income distribution that does not rely on arbitrarily fixed fractions of average EU GDP, as is currently used in EU cohesion policy (European Parliament and Council of the European Union 2021). This taxonomy is of interest beyond testing the assumptions of an OCA. As a novel strand of literature shows, regional economic decline in European regions is associated with the recent surge of far-right populism (Rodríguez-Pose 2018; Rodríguez-Pose et al. 2023). This decline is not only about inequalities in levels (i.e., “snapshot inequality”) at a specific point in time but also changes for prolonged periods in time. Maria Greve et al. (2023) show that economic decline even beyond the lifespan of people can contribute to the rise of the far-right through people’s collective memory. These “left-behind” places should roughly correspond to our peripheral cluster. In addition to economic fragility in a currency area, identifying those regions is thus crucial in understanding recent *political* instability as well.

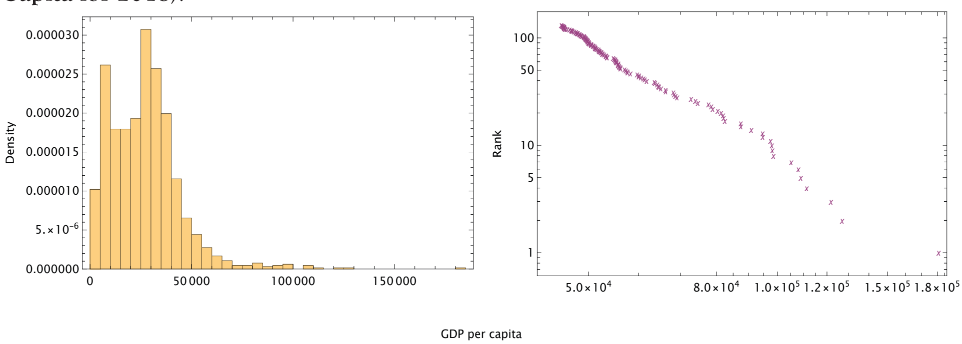
Notably, our proposed method relies only on the ensemble of observed GDP per capita levels to describe the growth dynamics and resilience capacities of regions. We do not use any additional information on unemployment rates or sectoral composition, which are often not available at sufficient granularity. Our proposed method is thus applicable to other contexts with limited data availability. Multidimensional analyses would also eventually necessitate a problematic and ultimately subjective weighting of these dimensions for composite indices (Rivera 2012). Even though we only rely on one variable, we generate a battery of results regarding both the taxonomy of regions and their growth dynamics. At the same time, this parsimonious use of data might also lead us to overlook important regional specificities if they are not well captured by GDP per capita. This is, for example, the case for Eastern Europe with relatively high shares of manufacturing in production but comparatively low levels of GDP per capita. We discuss this limitation in the section on results.

This article is organized as follows: in the following section, “Stylized Facts and Related Literature,” we describe our major explananda regarding the distribution of income in Europe and relate these to the extant literature on cumulative growth processes and dependency theory. We introduce our basic theoretical models in the section "Model" and show how both a Geometric Brownian motion with heterogeneous volatility components and a maximum entropy program lead to a mixture of two log-normal components. In the following section, "Data and Method," we describe the dataset we use to test our theoretical predictions and our estimation methods. We apply these methods in the section "Results" to show that we indeed find a mixture of two log-normal densities for the overall distribution of regional European GDP per capita levels that can be used to rigorously categorize regions into a core, semi-periphery, and periphery region. We conclude and discuss the implications of our findings in the final section," Discussion and Political Implications." The Appendix contains both the derivation of the results of the maximum entropy program (Appendix A) and some robustness checks of our empirical results (Appendix B).

Stylized Facts and Related Literature

We first set out to make the two relevant explananda—bimodal regional income distributions with heavy upper tail—more precise. To see these, consider figure 1. The left panel shows the frequency density of GDP per capita (GDPpc) levels on a regional level for the whole European dataset in 2018 and displays clear bimodality as our first stylized fact. On the right panel, we plot the rank-size or Zipf plot for the upper decile of observations on a double-log scale. Indeed, the relationship is approximately linear, indicating heavy-tailed behavior as our second stylized fact. Indeed, a fitted power-law cannot be rejected for various hypothesis tests for the upper 100 observations, as shown in Online Appendix.[1] Both stylized facts are present for the whole considered sample period, 2015 to 2018, and do not vanish for various robustness tests (i.e., limiting the dataset to only the European Union or the European Economic Area). They appear to be robust empirical regularities that we aim to explain within this article. We describe our used dataset in more detail in the section "Data and Method."

Figure 1. Stylized Facts of the European Income Distribution (measured as GDP Per Capita for 2018).



Note: The distribution is strongly bimodal in its bulk (cf. the left panel) and exhibits a heavy upper tail, as shown in the right panel, rank-size or Zipf plot of the upper decile of observations on a double-log scale.

[1] Supplemental data for this article can be accessed online at https://es.sonicurlprotection-mia.com/click?.

The bimodality of the distribution suggests two generating mechanisms behind its emergence. Since we are working at an interregional scale, a natural point of departure is the distinction between core and peripheral regions that has gained a lot of interest concerning Europe (cf., e.g., Gräbner et al. 2020a; 2020b). The heavy upper tail as the second stylized fact implies that the conditions of the Central Limit Theorem are likely violated, which would then lead to the emergence of a Gaussian distribution with thin tails. We conjecture that the assumption that growth increments are uncorrelated concerning levels is violated and that richer regions also tend to exhibit higher (absolute) growth increments. Indeed, it seems rather implausible that region A, with ten times the GDPpc compared to region B, would exhibit the same fluctuations of growth increments in currency terms. The most parsimonious adjustment to feature correlation between GDPpc level and GDPpc growth increments is to assume that, rather than those increments, growth *rates* are uncorrelated with levels, leading to stochastically multiplicative growth or success-breeds-success dynamics (Merton 1968). We empirically confirm the absence of a correlation between growth rates and levels, as well as the strongly positive correlation for absolute growth increments for our dataset.[2] Both the core/periphery distinction and this random multiplicative growth process trace back to a long tradition in heterodox economics that we briefly discuss in turn.

Traditional dependency theory emphasizes the taxonomy of countries falling either in the "core" or in the "periphery," with the economic development in the periphery being "conditioned by the development and expansion of" the core (Dos Santos 1970, 231). The main hypothesis is that this asymmetry is due to differences in the industrial composition of core and peripheral countries: while peripheral countries tend to produce primary goods like raw materials that are rather easily substitutable, the core countries produce sophisticated industrial products with much less scope for substitution. This leads to much more intense competition for peripheral than for core countries, letting the terms of trade for the periphery deteriorate. They receive fewer and fewer manufactured goods in (unequal) exchange for their primary goods (Prebisch 1950; Singer 1950). This unequal exchange underlines the necessity of coexistence between the core and periphery, as one cannot functionally exist without the other (Street 1987).

We build on this classification to argue that producers of primary goods face much more volatile growth paths than industrial producers since they are also much more exposed to fluctuations in world market prices. In our application, we understand peripheral regions to be peripheral relative to the European core, in line with the convention in the literature, such as in Claudius Gräbner et al. (2020a). This relative definition allows for significant manufacturing activity even in peripheral regions—we only require that these regions are relatively more reliant on primary goods production and thus exposed to world market prices. However, perhaps deviating from the convention in dependency theory, we argue that technologically sophisticated producers in the sense of César A. Hidalgo and Ricardo Hausmann (2009) and typically associated with the industrial core are also exposed to significant volatility. There are four reasons: first, financial hubs in the core might face rather high volatility, since financial markets are typically much more volatile than their non-financial counterparts (Mundt et al. 2014). Second, highly developed producers with high value-added might also face volatile growth, since their production of, for example, cars is

[2] For these results, please refer to Appendix B. Please note, however, that GDP levels are the result of many more accumulated realizations of a growth process than we can capture with our sample spanning only four years. Even though we can confirm our conjecture for the time period our dataset covers, we cannot test the hypothesis in a strict sense which would require a much more comprehensive dataset.

based on long and diversified supply chains that can amplify supply shocks and contribute to larger volatility (Acemoglu et al. 2012; Elliott et al. 2022). Third, in addition to this issue, technologically sophisticated production likely requires very specific inputs and production facilities that leave only limited space for substitution in response to those shocks. Fourth, and finally, the technological space at the World Technology Frontier is likely contested and subject to intense competition. This competition inherently also induces further volatility into regional growth paths.[3] In contrast to these two clusters of the core and periphery that we theorize to exhibit rather high volatility, the semi-periphery is characterized by low volatility and thus plausibly by an industrial structure that is focused on routine manufacturing.

However, while typical studies on core-periphery patterns typically rely on country-level data, we focus on European regions. This is an attempt to answer the "challenge of granularity" (Gräbner and Hafele 2020, 7) (i.e., the problem that regional idiosyncrasies are averaged away when considering only country-level data). Most prominently, as our analysis will also show, some regions in the North of Italy can plausibly be defined as part of a highly industrialized core, while the Southern "Mezzogiorno" is not as developed and can thus more plausibly be considered to be peripheral. Our results highlight that this is indeed an important oversight of country-level studies, with the success of common monetary policy crucially relying also on homogeneous development *within* countries. The rigorous taxonomy we propose might thus aid in tailoring policies for specific regions and regional development.

Our analysis focuses on differences in the second moment of the growth rate distribution by assuming equal expected growth rates.[4] We show that this parsimonious assumption, in conjunction with multiplicative growth, gives rise to the observed distributional patterns. The assumption of multiplicative growth is sufficient to generate a strongly skewed distribution of GDP levels, as it features a rich-get-richer phenomenon and, thus, path-dependent growth (Gibrat 1931; Kalecki 1945). This rich-get-richer mechanism is known by many different names according to discipline and school of thought, such as the "Matthew effect" in sociology (Merton 1968), "hysteresis" and "path-dependence" in evolutionary economics and evolutionary economic geography (Martin and Sunley 2006, for an overview) and "stochastically multiplicative growth" (Gabaix 2009) in finance and complexity economics. Institutional scholars will likely be most familiar with the closely related concept of (Circular) Cumulative Causation (Veblen 1898; Myrdal 1974; O'Hara 2008; Matutinovic 2020). All these ways of approaching the rich-get-richer phenomenon capture a process that is self-reinforcing or cumulative, albeit depending on different channels. Perhaps the most economically intuitive is the Kaldorian one, based on the vicious cycle of aggregate demand, income, and productivity growth (O'Hara 2008; Pressman and Holt 2008): productivity growth increases income, which in turn increases demand, leading to increases in productivity according to the Kaldor-Verdoorn law. For our taxonomy, we only propose a reduced-form representation of the growth process without settling for one specific interpretation.

By far the most common way to formalize this rich-get-richer phenomenon is random multiplicative growth (Gabaix 2009).[5] In the section "Model", we will elaborate on two ways

[3] We thank an anonymous reviewer for pointing us to these two last channels contributing to volatility in core regions.

[4] We do not necessarily think this assumption of equal expected growth rates is true in reality. Rather, we consider it to be a convenient analytical device to isolate the impact of different growth volatilities. This device allows us to show that the distributional regularity we observe in reality can be replicated even for equal expected growth rates, as long as volatilities between regimes differ.

[5] There exist other generating mechanisms for generating heavy-tailed distributions, most notably those based on hierarchical power e.g. within firms (Fix 2019). While this mechanism is certainly an appealing candidate

to capture this idea in more detail. Random multiplicative growth, also known as the *law of proportionate* effect in the literature (Gibrat 1931), implies in its most basic form that the expected growth rate of a given region does not depend on its GDP level (i.e., growth is scale-independent). Scale-independent growth rates are, for example, explainable by an arbitrage argument that combines a process of capital reallocation with diminishing marginal returns to scale (Schulz and Milakovic 2023): If a region temporarily exhibits higher (lower) returns than the cross-regional average, capital will flow (from) there and bring returns back to the average level due to diminishing returns to scale. Yet, given the differing degrees of exposure and volatility outlined above, this is a process of ceaseless fluctuations around this mean or a process of "turbulent arbitrage" (Shaikh and Jacobo 2020).

Our explanatory attempt thus focuses on growth volatility and not expected growth rates. This is not to say that the traditional explanations within dependency theory focusing on first moments are necessarily false when applied to the regional level. We argue that volatility and the ability of regional economies to absorb shocks are a fruitful and neglected dimension to explain interregional disparities, which is proxied by the realized volatility of growth rates in GDPpc.

Model

Our modeling strategy aims to capture regional growth paths using a reduced-form stochastic representation for each county.[6] We use both the formalism of a stochastic growth process in the form of a Geometric Brownian Motion and the Maximum Entropy program to capture the path-dependent nature of the growth process that the heavy upper tail of the regional income distribution implies. As we will show, both formalisms imply the same type of stationary distribution, highlighting the crucial relevance of path-dependent or multiplicative growth. Our representation favors parsimony over a detailed description and focuses on the outcome variable of GDP per capita rather than the myriad of factors outlined above that might influence economic growth. This parsimonious modeling strategy, however, immediately invites two criticisms that we want to discuss briefly before detailing the precise formalism: First, GDP per capita is a rather crude measure of economic well-being that does not take distribution into account (Myrdal 1974). We opt for the GDP per capita measure, since it is already calculated at a rather granular level that captures the between-component of income inequality in Europe. Empirically, GDP per capita also appears to correlate quite well with other measures of well-being (Jones and Klenow 2016) and is hence the major target variable for EU cohesion policy (European Parliament and Council of the European Union 2021). Second, by construction, a representation of dependency theory that posits independent growth processes per region cannot take the underlying interdependency of regions into account that gives rise to core-periphery structures in the first place (Myrdal 1974; 1978 and Kvangraven 2021, for a review). Indeed, there is no explicit dependence between regions in the formalisms elaborated below; dependencies are only considered as latent, unobservable variables. We would argue that the volatility parameter of the growth process is a proxy for those interdependencies that dependency theory highlights, in the sense that strong dependency on primary products causes rather volatile growth paths as

for the personal income distribution, given the ubiquity of both power laws and hierarchical structures, it is unclear what the analogon of this hierarchy would be on the regional level. We thus stick to a generating mechanism represented by a random growth process.

[6] Throughout the text, we consistently refer to the basic unit of the NUTS-3 classification explained below in section 4 as a "county" even though national naming conventions might differ from our use.

an outcome variable. In this sense, we focus on the effects, rather than the precise causes of dependency that are nevertheless important avenues for further research to specify which exact mechanism could cause these differences in volatility.

Geometric Brownian Motion

The above qualitative discussions on sectoral composition lend themselves to being formalized as growth following two distinct Geometric Brownian Motion (GBM) processes. The GBM process is well-suited to represent path-dependent growth, since the growth differential *dY(t)* depends on the GDP level *Y(t)*. In addition, the structural taxonomy according to core, semi-periphery, and periphery implies different volatility regimes. Both core and periphery are assumed to follow growth processes with relatively high volatility, albeit for very different reasons: while the core counties exhibit industrial structures with a focus on finance and technologically sophisticated products, the reliance of peripheral counties on raw materials and thus world prices makes those growth processes more volatile.

We formalize this argument by postulating that core and peripheral counties *i* follow a GBM process *H* with high volatility for their GDP per capita . By contrast, semi-peripheral counties *j* follow a GBM process *L* with low volatility for their GDP per capita . Assuming equal drift terms μ for simplicity, this implies these two stochastic differential equations,

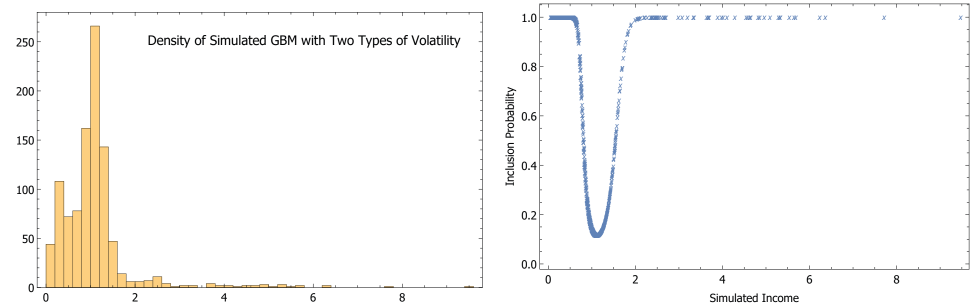
$$dY_i^H(t) = \mu Y_i^H(t)\,dt + Y_i^H(t)\,\sigma^H\,dW_t \qquad (1)$$

and

$$dY_i^L(t) = \mu Y_i^L(t)\,dt + \sigma^L\,Y_i^L(t)\,dW_t, \qquad (2)$$

with t ≥ 0 as time periods,[7] *dW* as Wiener increments, and $\sigma^H > \sigma^L$. Since the stationary distribution of any *Y* for any initial value *Y(0)* with *t* sufficiently large converges to a log-normal distribution (Gibrat 1931; Kalecki 1945), we expect that the resulting distribution of our economy characterized by $N^H \in N$ counties of type *H* and $N^L \in N$ counties of type *L* will follow a mixture of two log-normal distributions. The higher volatility in the growth of type *H* counties by > will eventually manifest as counties being pushed towards the upper and lower tails of the overall distribution of Y, with the low volatility counties populating the remaining segment between these two tails. This is what we indeed observe, simulating a discretized version of (1) and (3) with $N^H = N^L = 500$, initial values equal for all *i* and *j* as *Y(0) = 1*, *μ = 0.01*, σ^H = 0.3, and σ^L = 0.05 after 1,000 time steps.

Figure 2. The density of simulated GBM with two volatility types (left panel) and the inclusion probability in the estimated log-normal component with high variance.



[7] Since our dataset is based on annual observations, t thus measures the number of years after some initial period.

Maximum Entropy

The Maximum Entropy approach is an information-theoretical concept introduced by Edwin T. Jaynes (2019) and based on C. E. Shannon (1948). Shannon's entropy differs from the use of the laws of thermodynamics in economics (Georgescu-Roegen 1971), as well as from traditional methods in economics. The Maximum Entropy method is an analytical device to infer the combinatorial most likely distribution from a known moment constraint or set of moment constraints. For example, assuming an arithmetic mean constraint (i.e., that the mean level and consequently total sum of a variable is conserved in the growth process) leads to an exponential distribution of the variable in question as the entropy-maximizing solution. This is a consequence of Jaynes' concentration theorem, which states that the overwhelming majority of distributions that are compatible with the assumed constraints exhibit maximum entropy ([1978] 1989). Jaynes' theorem implies that it is extremely unlikely for a distribution with a specific functional form, constraints other than those implied by Maximum Entropy inference are responsible for their emergence.

The entropy function gives a degree of dispersion of a variable, which considers the degree of organization of the system. A highly ordered system has a lower entropy compared to a system with fewer constraints and more uncertainty. To maximize the entropy under the assumptions induced by the researcher implies that we assume everything else besides the constraints is as uncertain as possible. Therefore, the number and design of the constraints on a system have an impact on the solution of the entropy maximization.

In information theory, all underlying assumptions of the model must be explicitly stated to derive a distributional form for a variable. This transparency is not only necessary for the approach itself; it is also honest towards the research community as it discloses all theoretical assumptions and contributes to full transparency. Only explicitly stated assumption find their way into the final functional form, as Maximum Entropy leads to the least-informed possible distribution. The least informed distribution is not an educated guess, as the name might imply, but rather the distributional form that contains the least information besides the data. The model consists only of the economically reasoned assumptions and the implied uncertainty beyond their constraints.

Based on a first visual inspection of the data, the bimodality of the GDPpc distribution is striking. Therefore, we consider a two-component mixture distribution to adequately capture the underlying data-generating process. The Gaussian distribution of the logarithmic GDPpc appears to be particularly plausible as it comes from two important properties of the area under observation. First, we rule out that GDPpc in itself is the result of additive growth: Income levels are not reassigned for every period but rather depend on the level in previous periods, indicating the relevance of capabilities that are already in place. Second, as long as this *multiplicative* growth process has a finite variance in growth rates without any further constraints (Thurner et al. 2018), we will observe a log-normal distribution. Even when growth rates are mesokurtic, the resulting stationary distribution features a heavy tail.

Since Shannon's entropy is defined by

$$H(x) = -\int_0^\infty p(x)\log p(x)\,dx, \tag{3}$$

and the probability density p(x) has to integrate to unity; the Maximum Entropy problem is well defined and can be solved by applying a Lagrangian.

$$\mathcal{L}((p(x),\lambda\_i) = -\int_0^\infty p(x)\log p(x)\,dx - \lambda_1(\int_0^\infty p(x)\,dx - 1) \tag{4}$$

$$-\lambda_2\left(\int_0^\infty p(x)\log x\,dx-\mu\right)-\lambda_3\left(\int_0^\infty p(x)(\log x-\mu)^2dx-\sigma^2\right)=H(p^*(x)) \quad (5)$$

Apart from the normalization constraint for all probability densities corresponding to λ_1, the two constraints with Lagrange multipliers λ_2 and λ_3 relate to the logarithm of the random variable *x* or GDPpc in question and thus to the relevant growth rates. The two constraints with multipliers λ_2 and λ_3 can thus be interpreted as defining a common expected rate of growth (constraint number 2) with the growth rate distribution showing fixed finite variance (constraint number 3). These two assumptions are the only two assumptions that we include in our Maximum Entropy model. We show in Appendix A that this optimization problem is solved by the probability density function *p*(*x*) of a log-normal distribution. Here we also show that the standard deviation of growth rates expressed in constraint no. 3 relates directly to the standard deviation of the emerging log-normal distribution, much like for the GBM specification. The mixture of two log-normal densities thus also emerges for the maximum entropy program, whenever we suppose differently volatile stochastically multiplicative growth processes.

If we were to change the constraints for the maximum entropy program, we would derive a different distributional form (Golan 2017). The data having a well-defined finite mean and variance would, for example, lead to a Gaussian normal distribution. If we remove the assumption of a well-defined variance to allow for a large variation in the data and require the data to be positive, we will derive the exponential distribution. Since all of the presented options here are plausible candidates, we test all six combinatorial possibilities to fit the data.

The general model of Maximum Entropy can be estimated with Bayesian and frequentist methods. As we consider the probabilities in the data as degrees of beliefs and, due to the short time period of available data, not as long-run frequencies, we estimate the models using Bayesian methods (Giffin and Caticha 2007; Scharfenaker and Yang 2020). Applying the maximum entropy approach to empirical data, the outcome of political decisions and evolutionary trends provides a researcher with a broader range of analytical tools than other types of economic modelling. Since the observed (and estimated) distribution is the one maximizing entropy, we know that our model is complete in the sense that adding additional assumptions or removing them from the maximum entropy model would not produce better results. The model does not lack essential features or is overfitting (Golan 2017). The maximum entropy approach implies maximal uncertainty about the model beyond its explicitly stated features. The explicit claims regarding a log-normal distribution are the non-negativity and the existence of multiplicative growth. This contrasts with the widely spread idea in economic analysis that uncertainty must be spread over all parameters that are needed to fully explain the model, as it is achieved in regression analyses. The uncertainty within the model classifies it as a true parsimonious model as it efficiently uses the uncertainty as a feature rather than a shortcoming in data analysis (Shannon 1948; Jaynes 2019). A supra-national entity that would (or at least attempt to) redistribute all income equally over all people would counteract the systemic development and lead to a different distributional form, but not change the fundamental dynamics themselves. We classify constraints as systemic, but policy measures as changes within the system.

The constraints of a system are general and define the environment in which political decisions are possible. An analogy for this would be a car racetrack: The conditions of the system define the track; guardrails limit the possibilities of what is possible for the cars. Regulations, however, define the rules of the race as they set speed limits and define unsporting behavior. How the cars and driver behavior on the racetrack therefore depends on the systemic conditions and in-system regulations. Similar reasoning can be applied to our understanding of the European regional system: Regions develop according to fundamental constraints that we interpret as reflecting different industrial compositions, leading to differences in realized volatility. We consider these to be systemic. Policy can directly intervene by redistributive measures, but will have to do so in every period, since the fundamental constraints will lead the system to the same stationary distribution we observe. Only an industrial policy that focuses directly on industrial composition and specialization patterns has the potential to change these fundamental constraints, making constant redistribution perhaps less necessary. An example of such an industrial policy would be to strategically position industries to equalize growth capacities. We will return to this aspect in the section "Discussion and Political Implications."

Data and Method

The European Union provides exhaustive data for the socio-economic environment in its member states and regions. This data is available at different levels of granularity to allow for an improved and coherent insight across all members, candidates, and counties that are part of the European Free Trade Agreement (EFTA). Those NUTS-levels define the level of disaggregation. While NUTS-1 includes the whole country for smaller countries, larger countries are separated into several NUTS-1 regions. France, for example, reports for 14 regions and overseas departments, and Germany reports for its sixteen states. NUTS-2 is the next smaller administrative level, and NUTS-3 is the smallest non-local administrative unit. For most countries, data available on NUTS-3 level represents county-level data.

In our analysis, we rely on the Gross Domestic Product data at market prices per capita (GDPpc) on a NUTS-3 level.[8] The data was taken from the official Eurostat homepage and is labeled with the data-code *nama_10r_3gdp*. For consistent estimates, we concentrate on a coherent period of time for which data coverage does not change. Since for nearly all departments in France, data for 2014 and before are not available, and data for 2019 and later have, in general, not yet been released, our analysis concentrates on the time period between 2015 and 2018. Those years also represent a relatively quiet period of macroeconomic shocks on the European continent, covering the time between the debt crisis and the turbulent and unprecedented times of COVID-19.

For all our estimations, we use the R-package *rstan*, provided by the Stan Development Team (2021).[9] In a first step, we determine the most likely structural form for the distribution of GDPpc. We provide standard econometric tests and informational indicators to specify which model suits the available data best. As we can identify the bimodal empirical distribution as a two-component mixture distribution, we can assign each NUTS-3 region based on Bayes' Theorem a probability to belong to one or the other component. In a third and final step, we use the characteristics of a region concerning its volatility regime and absolute value in GDPpc to provide an indicator for the different clusters of core,

[8] For our analysis, real GDP per capita rather than GDP per capita at market prices would be more appropriate Yet, Eurostat unfortunately does not have price indices at the most granular regional level. Since all GDP per capita levels in our dataset are denoted in the same currency, we nevertheless hope to be reasonably safe here, especially since our dataset only covers a very short time period.

[9] We use three chains with 10,000 iterations and 1,000 burn-ins each (Gelman et al. 2004).

semi-periphery, and periphery. To our knowledge, such a county-level indicator based on empirical data has not been presented in the literature yet.

Results

One Mixture

As previously mentioned, we estimate a two-component mixture distribution based on the visually observed bimodality. We test the assumptions of two log-normal, two normal, two exponential, and the mixture of two different distributions against the empirical data. The exponential and log-normal distributions appear to be somewhat natural candidates, as they exhibit a higher skewness than the Gaussian and support only over the positive real half-line. We include the Gaussian, since Gaussian mixtures are the standard in the literature (Pittau et al. 2010), even though both stylized facts rule them out, as the Gaussian is both unimodal and exhibits no fat tails. We also do not consider Pareto distributions, since they require the tail to span at least two orders of magnitude to properly distinguish them from other candidate distributions (Stumpf and Porter 2012), which our data does not (cf. figure 1). Overall, this gives us six possible combinations within a two-component mixture distribution. Note that our parsimonious models unanimously imply a mixture of two log-normal distributions if Gibrat's law of growth holds and growth rates are independent of levels.

It is not our goal to verify a predetermined assumption about the nature of the data but rather to derive the most likely solution. Table 1 presents our effort to test all six possible distributions against the empirical data. We concentrate on the most common tests in the statistical literature, the Kullback-Leibler divergence (KLD), Kolmogorov-Smirnov (KS), Anderson-Darling (AD), Cramér-von Mises (CvM), as well as AIC and BIC to account for the different number of parameters in the models.

Table 1. In 22 out of 24 considered hypothesis tests, the mixture of two log-normal distributions provides the best fit for the empirical data.

	KLD	KS	AD	CvM	AIC	BIC
2015	LN/LN	LN/LN	LN/LN	LN/LN	LN/LN	LN/LN
2016	LN/LN	LN/LN	N/N	LN/LN	LN/LN	LN/LN
2017	LN/LN	LN/LN	LN/LN	LN/LN	LN/LN	LN/LN
2018	LN/LN	LN/LN	N/N	LN/LN	LN/LN	LN/LN

For nearly all years and tests, the two log-normal mixture model (LN/LN) provides the most accurate description for the underlying data. For all considered years, it also cannot be rejected at the usual significance levels for three standard distributional fit tests (cf. table 2), particularly also for the cases where the Anderson-Darling test prefers the mixture of two Gaussians.

To further fix notation, let the probability density of the log-normal/log-normal mixture be defined as

$$p(y) = \theta \frac{\exp\left(-\frac{(\log y - \mu_1)^2}{2\sigma_1^2}\right)}{\sqrt{2\pi}\,\sigma_1 y} + (1-\theta)\frac{\exp\left(-\frac{(\log y - \mu_2)^2}{2\sigma_2^2}\right)}{\sqrt{2\pi}\,\sigma_2 y} \tag{6}$$

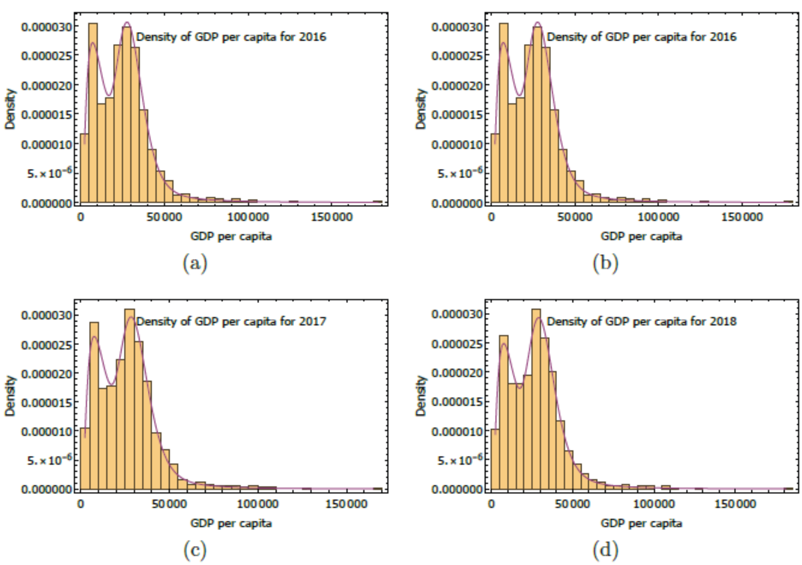
with $\theta \in [0,1]$ as the mixture parameter, μ_1 and μ_2 as location parameters, and σ_1, $\sigma_2 > 0$ as dispersion parameters of the two underlying log-normal distributions. Parameter estimates fluctuate only very little between years. Especially, the mixing parameter θ remains roughly constant, indicating that no significant disturbances to the structure of the economic environment occurred. We discuss this parameter further in Online Appendix B. Analyzing a longer time period might be beneficial to address structural developments that are beyond the scope of this article. The estimated parameters testify to the robustness of our argument, which also implies stable economic conditions with differing degrees of volatility. This is especially obvious from the different dispersion parameters $\sigma_1 >> \sigma_2$ for the estimated *size*, hinting also at differing *growth* volatilities.

Table 2. The log-normal/log-normal mixture cannot be rejected for any given year according to the three distributional fit tests at the usual levels of significance.

	KS		AD		CvM	
2015	0.342232	(***)	0.467545	(***)	0.59341	(***)
2016	0.437714	(***)	0.465474	(***)	0.597986	(***)
2017	0.379998	(***)	0.339621	(***)	0.43011	(***)
2018	0.499479	(***)	0.437892	(***)	0.63037	(***)

Besides providing statistical evidence, we want to highlight the accuracy of the LN/LN model compared to the empirical data in Figure 3. The theoretical fit of the LN/LN model is striking, showing that our model indeed seems to capture the empirical data-generating process well.

Figure 3. Densities of GDP per capita for all regions with superimposed fit for log-normal/log-normal mixture (2015—2018).



Two Regimes of Volatility

Since we observe a two-component mixture for one dataset, assigning each observation a probability to be part of one of those two distributions is possible. As we know that a specific region is part of the dataset, we also know that the probability that region A is in distribution LN1 is the counter probability that the region is in distribution LN2. This allows us to assign each region to a probability regime based on the likelihood that the specific region belongs to the underlying distribution. In a final step, we assign an observation to the distribution to which it is more likely to belong, implying a cut-off probability of 0.5.

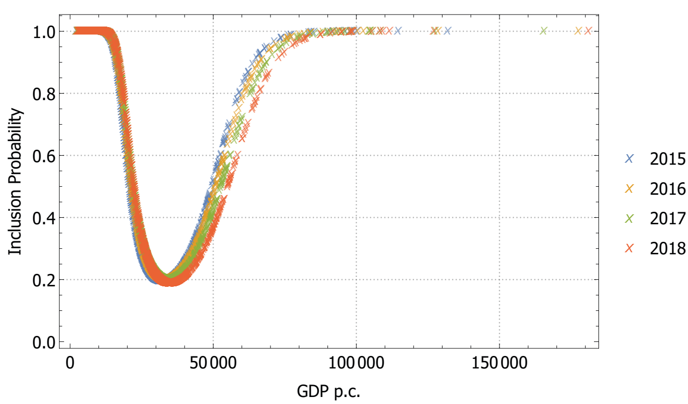
Inspired by the work of Ellis Scharfenaker and Gregor Semieniuk (2015), we apply Bayes' theorem to determine to which component of the mixture distribution (LN1 or LN2) each observation *c* belongs. The probability that we observe LN1 based on observation *c* is equal to the joint probability of the occurrence of LN1 (which is given through the mixing parameter) and the observation *c*, divided by the probability of observation *c*:

$$\begin{aligned} p(LN1 \mid c) &= \frac{p(c, LN1)}{p(c)} \\ &= \frac{p(c, LN1)p(c \mid LN1)}{p(LN1)p(c \mid LN1) + p(LN2)p(c \mid LN2)} \\ &= \frac{\Phi_1 LN(c \mid \mu_1, \sigma_1)}{\Phi_1 LN(c \mid \mu_1, \sigma_1) + \Phi_2 LN(c \mid \mu_2, \sigma_2)} \end{aligned} \tag{7}$$

Since we already estimated the parameter of the mixture distribution, it is straightforward to plug in the estimated values and determine the probability for each observation belonging to LN1 and LN2 vice versa. We observe for all years a U-shaped relation between the GDPpc and probability belonging to LN1. Figure 4 illustrates how regions with a high or low GDPpc belong to LN1, while regions with a medium-range GDPpc belong to LN2.

As shown in the subsection "Geometric Brownian Motion," this indicates that two regimes of volatility characterize the NUTS-3 regions in Europe. A high volatility cluster consisting of low and high GDPpc, separated by a low volatility cluster covering the middle GDPpc regions.

Figure 4. Probability of each region being part of LN1, depending on income. For all four years, we see a clear U-shaped behavior.



Three Clusters of Inequality

In a final step, we consider the two regimes of volatility and the absolute value of GDPpc for the NUTS-3 regions in Europe to determine a data-driven indicator for a small-level separation into core, semi-periphery, and periphery. As we have separated all regions into two regimes of volatility in the previous step, we use the fact that high and low GDPpc regions are in the same component of the mixture model. We therefore classify high volatility/high GDPpc regions as the core, low volatility regions independent of their GDPpc as semi-periphery, and high volatility/low GDPpc regions as periphery. Furthermore, we use the ends of the U-shaped graph to indicate periphery and core, which are, in line with the literature (Zhao 2021), separated by the semi-periphery in the lower U-shape of the graph.

Those indeed appear to reflect structural differences, as the inter-regime mobility is close to nil. In table 3, we report the transition rates between the three regimes for the time period between 2015 and 2018. There exists virtually no "large jumps" between 2015 and 2018, and no region transitioned from the periphery to the core or vice versa. There is some mobility between adjacent regimes (i.e., between the periphery and the semi-periphery, and the semi-periphery and the core), but even this type of mobility is very low. In general, the low off-diagonal elements of the matrix suggest that regions appear to persist in their respective regimes, indicating that we indeed capture economically meaningful properties of their growth processes. The core is by far the most mobile cluster, with more than 10% of regions dropping out of this category in three years. This finding might be considered as evidence for the conjecture that the technological space in which producers located in the core operate is a highly contested one (Gräbner et al., 2020a).

Table 3. Mobility between regimes for NUTS-3 regions between 2015 and 2018 in percent. Mobility is generally very low and only occurs between adjacent regimes.

		2018		
		Periphery	**Semi-Periphery**	**Core**
2015	Periphery	97.14	2.86	0.00
	Semi-Periphery	0.69	98.89	0.42
	Core	0.00	10.29	89.71

The generally rather low mobility allows us to present a data-driven overview of the regional European economic structure. For an optimal visual representation, Figure 6 is color-coded, representing the different structural components (Popović n.d.). Two major implications of this classification are immediately obvious: First, the peripheral regions according to our classification tend to be indeed located at the geographical periphery of Europe. This is perhaps consistent with the agglomerative effects predicted in orthodox New Economic Geography (Krugman 1991). Eleonora Cutrini et al. (2022) indeed find limited evidence for the agglomeration thesis on an industrial level of disaggregation that is, however, conflicting and depends on the country context and considered period. Second, we confirm this finding of a mere tendency for agglomeration and document a large degree of interregional variation. In several countries, such as France, Germany, and Italy, all three types of regions exist, pointing to the limits of country-level classifications. Even geographical development axes that explicitly aim to transcend national borders appear to be insufficient to capture this heterogeneity: while a majority of core regions are indeed located within the famous "Blue Banana," from Milano to Brussels (Hospers 2003), clearly not all regions here are within the core.[10] The set of regions that are classified as the core is rather unsurprising, though. Their high degree of integration into the world economy through their leading economies like finance, the automotive sector, or oil, a high GDPpc appears to come at the cost of high volatility. Examples here are Luxembourg, Wolfsburg, Munich, and Milano. The industrial compositions of these regions are perhaps equally outward-looking as the peripheral ones and dependent on international commodity and capital markets. However, these regions appear to be net beneficiaries from the relatively high induced volatility. Particularly, those regions specializing in financial products should experience volatile growth paths since volatility in financial markets is typically one order of magnitude higher than in commodity or service markets (Mundt et al. 2014). Note also that core regions appear to be disproportionately urban, with the proximity to university and research institutes fostering the development of such highly complex products (Broekel 2019). Apart from these known industrial centers, the remaining core regions are primarily located in the Republic of Ireland (especially in 2018) and Norway (especially in 2015). The mobility here is comparatively high, underlining the argument that the core regions also suffer from high induced volatility. In those two cases, the volatility likely stems from country specifics (i.e., the relevance of energy production and oil exports in Norway that are exposed to developments at the world market or the financial sector orientation of the Republic of Ireland).

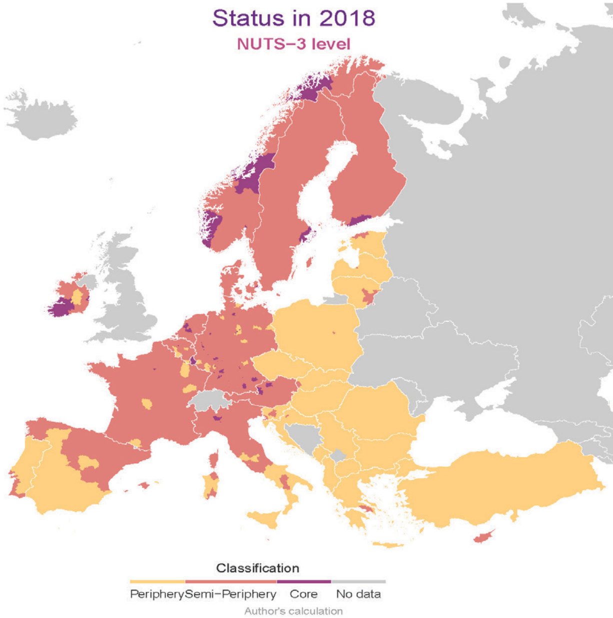
The semi-periphery is composed of regions in central Europe that are known for their high economic performance but not necessarily for specialization in a specific product. A larger variety of industries in those regions might balance external shocks from the world market in individual industries. It is also possible that these regions do not feel the same exposure to world market shocks to the core industries, as their involvement in those industries is secondary, by purely supplying input factors.

Finally, the peripheral countries will tend to produce primary products and are thus much less able to absorb external shocks. This is because substitutability of primary goods is generally high, leaving producers of these goods with a relatively low market power and thus exposed to price developments on the world market (Prebisch 1950; Singer 1950).

While our results appear to be plausible for most parts of Europe, Figure 5 shows that our taxonomy puts essentially all of Eastern Europe into the peripheral category. Given the fact that many Eastern European regions are engaged in "routine" manufacturing activities (Stöllinger 2016), this should put them into the semi-periphery. This issue highlights the limitations of our approach based on GDPpc levels—production levels in post-Soviet states and regions after the initial "transition decline" might simply not have caught up to other European regions, even though their sectoral compositions and even growth rates are similar to other regions classified as semi-periphery (Milanovic 2015). In the classification of the extant literature, these states would likely be put into the category of "catch-up" regions (Gräbner et al. 2020b), with rather low levels of GDPpc but high growth (potential) that our level-based classification cannot account for by construction. The experience of those regions should thus serve as a cautionary tale against overly generalizing from one measure and calls for further research into the multidimensional origins of core, semi-peripheral, and peripheral structures.

[10] The original "Blue Banana" also spans Northwest England that is not covered in our sample.

Figure 5. Visualization of the regions under consideration and their classification into core, semi-periphery, or periphery for the year 2018



Note: The maps for all other years under consideration are presented in Appendix B.

Discussion and Policy Implications

The short period of observation does not allow for an in-depth evaluation of the efforts by the European Union to create parity in living standards. It does, however, allow for warnings towards any such policies. It is crucial to take the different characteristics in Europe into account and how those regions are connected. Besides the GDPpc for a region, it is important to consider the volatility a region faces in its growth trajectory. A region in the south of Spain might be more similar to Poland than a region in the north of the country with respect to its structural foundation. These inter-country differences in capabilities have to be acknowledged by economic policy. In particular, the different growth trajectories according to the three proposed clusters imply that the considered ensemble of regions is far from an OCA that would require approximately homogeneous regional development.

While much of the literature has focused on the expected rate of growth on a national level (Gräbner et al. 2020a), our approach is more granular. It underlines the importance of the second moment of growth rate distributions (i.e., volatility). We show that stochastically multiplicative growth, either formalized by a Geometric Brownian Motion or by solving the corresponding maximum entropy program, can replicate the observed distributional patterns with the minimal additional assumption that there are structural differences in volatility between regions.[11] Our reduced-form representations are far from a full-fledged

[11] Stochastically multiplicative growth refers to a growth process, where growth increments are random ("stochastic") and where they depend on previous levels ("multiplicative"). By contrast, for an additive growth

growth model; still, we argue that such a full-fledged regional growth model must be *observationally equivalent* to the stochastic representation we propose.

As previously mentioned, the applied Maximum Entropy and GBM approach rejects any potential claims that the current political framework of the EFTA ensures or even promotes a uniform standard of living across its regions. As the observed distribution is derived under the assumption of GDPpc, which depends on mesokurtic developments of income level, a redistribution effect that correlates with the GDPpc in a specific region can be ruled out. Such a redistribution would essentially amount to progressive taxation. This becomes intuitively clear when considering the implications of the Maximum Entropy approach, as under the given constraints, no other emergent stationary distribution than a log-normal distribution is possible. For our postulated theoretical data-generating process, any specific realization of growth rates will eventually (asymptotically) converge to a log-normal distribution. In this sense, our proposed reduced-form growth process implies that the regional development in Europe is inherently polarizing.

This point cannot be stressed enough, as it highlights the difference between systemic and within-system changes. While constant redistribution does not address the fundamental data-generating process, it changes the outcome through active intervention. If the process of redistribution ends, the distribution of GDPpc will again be (asymptotically) log-normal. This observation lends itself directly to a taxonomy of policy measures: Any temporary redistributive scheme will not change the systemic nature of the growth process with the log-normal as an attractor and is thus fundamentally unable to provide equality across regions. By contrast, policies that alter the constraints of the system (e.g., by appropriate industrial policy or an entrepreneurial state activity) (Dawid et al. 2014; Dosi et al. 2023), in principle, can generate any stationary distribution of regional income levels. Our results suggest that such changes to the system must address the capability to absorb shocks in all NUTS-3 regions by equalizing the industrial composition and therefore the volatility regime. Rather than merely providing transfers, place-based (industrial) policies should enhance opportunities for specific regions (Rodríguez-Pose 2018). This normative conclusion is consistent with several other findings in the literature that also point to the importance of the technological gap rather than, for example, labor market institutions for convergence (Botta and Tippet 2022).

Our investigation has not just provided new and additional insight into the inequality between different regions in Europe, but also contributes to the problematic and often coarse-grained differentiation of regions into growth and performance-oriented regimes. Specifically, we provide a data-driven approach that classifies all regions on a NUTS-3-level in a core, semi-periphery, and periphery framework. We hope that our work will contribute to more informed discussions and policies to achieve a uniform standard of living in Europe.

Disclosure Statement

No potential conflicts of interest were reported by the authors.

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