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Economic Growth in European Regions: Divergence within Convergence

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Master's Thesis

Prague, August 2022

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Declaration of Authorship

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Proposed Topic:

Economic Growth in European Regions: Divergence within Convergence

Preliminary scope of work:

Research question and motivation

I aim to review the economic convergence of European regions which has been at the center of a set of articles (for instance, Abreu, de Groot, and Florax 2005; Esposti and Bussoletti 2008; Cappelen et al. 2003; Fagerberg and Verspagen 1996). The European Union (EU) has launched several support programs based on different characteristics of regions (Cappelen et al. 2003). The impact of these programs can be hard to determine and controversial (Cappelen et al. 2003; Fagerberg and Verspagen 1996; Ramajo et al. 2008). However, determining the effects of support programs are crucial for authorities and determine the economic well-being of regions. Thus, empirical evaluation is an important issue for policymaking. Innovations and innovativeness arguably have a strong effect on the growth of regions (Fagerberg and Verspagen 1996). The objective of this study is to econometrically measure the effects of support programs and to compare them in different regions. The comparison will allow discussion of regional differences and policy implications for the particular cases.

Contribution

There are several articles devoted to regional economic convergence in the EU. While some use a more classical OLS approach (Fagerberg and Verspagen 1996; Cappelen et al. 2003), some also consider spatial models (Ramajo et al. 2008). However, I do not know any work which has performed econometric analysis of convergence for multiple regions and then compared the effects of programs. This study aims to contribute to this area of research. My aim is to revise GDP per capita convergence and divergence evidence in the EU using different measures, including standard deviation and a beta convergence model. I intend to check if income convergence was stable in the EU in 2000 – 2018.

Methodology

I aim to develop mostly empirical work. Thus, my focus will be primarily on statistical analysis in the form of regression analysis. I will use data from Eurostat which provides data on various socio-economic characteristics for members of the EU on the regional level. For instance, I will use GDP per capita, unemployment level, employment in agriculture and other socio-economic indicators in spirit of Fagerberg and Verspagen (1996). An additional possible data source is the CORDIS database which covers data on European innovative projects.

The empirical part of my research will consist of two parts: growth convergence in the EU in general and in particular regions of the EU. The former part will measure the effect of investments, innovations, and support programs on the convergence of European regions. The latter will compare the same effects in several regions both among themselves and for the EU. The results of the comparison will serve as a basis for further discussion.

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List of academic literature:

Bibliography

Abreu, M., H.L.F. de Groot, and R.J.G.M. Florax. 2005. "A Meta-Analysis of β-Convergence: The Legendary 2%." *Journal of Economic Surveys* 19 (3): 389–420. https://doi.org/10.1111/j.0950-0804.2005.00253.x.

Cappelen, A., F. Castellacci, J. Fagerberg, and B. Verspagen. 2003. "The Impact of EU Regional Support on Growth and Convergence in the European Union." *Journal of Common Market Studies* 41 (4): 621–44. https://doi.org/10.1111/1468-5965.00438.

Esposti, R., and S. Bussoletti. 2008. "Impact of Objective 1 Funds on Regional Growth Convergence in the European Union: A Panel-Data Approach." *Regional Studies* 42 (2): 159–73. https://doi.org/10.1080/00343400601142753.

Fagerberg, J., and B. Verspagen. 1996. "Heading for Divergence? Regional Growth in Europe Reconsidered." *Journal of Common Market Studies* 34 (3): 431–48. https://doi.org/10.1111/j.1468-5965.1996.tb00580.x.

Ramajo, J., M.A. Márquez, G.J.D. Hewings, and M.M. Salinas. 2008. "Spatial Heterogeneity and Interregional Spillovers in the European Union: Do Cohesion Policies Encourage Convergence across Regions?" *European Economic Review* 52 (3): 551–67. https://doi.org/10.1016/j.euroecorev.2007.05.006.

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Prague, Czech Republic Egor Iankov

August, 2022

Abstract

I study the convergence and divergence in the EU regions in 2000 – 2018. I use data on the GDP per capita and modeled real expenditures under EU support schemes of regions from the EU members at the NUTS2 level of disaggregation. I apply β-convergence model to this setting. I show that the overall dispersion of regions has increased since 2003 almost without interruptions. If I include country dummies, the variation of GDP per capita decreases on average in 2000 – 2010. This result does not fully agree with the regression analysis of compound growth rates and log initial GDP per capita. However, this discrepancy is explained by the entry of new regions and the blending of particular groups of regions in 2018. I find that EU member countries diverge from each other, but regions within each country converge to the country mean. Further analysis shows that convergence is robust to the inclusion of regional characteristics and EU support. My results show that the EU Cohesion Policy is only partially successful in promoting convergence of the EU regions.

Keywords: β-convergence, EU Regional Policy, Cohesion Policy, GDP per capita

Abstrakt

Studuji konvergenci a divergenci v regionech EU v letech 2000-2018. Používám údaje o HDP na obyvatele a modelované reálné výdaje v rámci režimů podpory EU regionů z členských zemí EU na úrovni členění NUTS2. Na toto nastavení aplikuji model β-konvergence. Ukazuji, že celková disperze regionů se od roku 2003 téměř bez přerušení zvyšuje. Pokud zahrnu fixní efekty v rámci jednotlivých zemí, rozptyl HDP na obyvatele se v letech 2000-2010 v průměru snižuje. Tento výsledek není zcela v souladu s regresní analýzou složených temp růstu a logaritmického počátečního HDP na obyvatele. Tento nesoulad je však vysvětlitelný vstupem nových regionů a prolínáním jednotlivých skupin regionů v roce 2018. Zjistil jsem, že členské země EU se od sebe navzájem liší, ale regiony v rámci jednotlivých zemí konvergují k průměru zemí. Další analýza ukazuje, že konvergence je robustní vůči zahrnutí regionálních charakteristik a podpory EU. Mé výsledky ukazují, že politika soudržnosti EU je při podpoře konvergence regionů EU úspěšná pouze částečně.

Klíčová slova: β-konvergence, regionální politika EU, politika soudržnosti, HDP na obyvatele.

1. Introduction

The issue of economic growth plays a pivotal role in contemporary life (Rodríguez-Pose 2013); it affects the quality of life and is viewed as an indicator of the success of society. One of the main ways to promote economic development is investments (Rodríguez-Pose 2013). Thus, some authorities implement measures such as financial support to lagging regions to increase growth. However, for large entities, not only overall growth matters but also equality of regions. For instance, the European Union (EU) has created structural funds to support the convergence of its regions.

Many researchers have studied economic growth and GDP convergence in the EU. For instance, Cappelen et al. (2003) study European regions in terms of their growth and influence of European support funds. Fagerberg and Verspagen (1996) use a similar approach. Cappelen et al. find that there is a meaningful division of regions based on the type of received support. Secondly, regional support indeed contributes positively to growth on a regional level. Consequently, structural funds also promote equality among European regions. However, the degree of this promotion is region-specific. Cappelen et al. show that underdeveloped regions cannot use financial aid with the same efficiency level, while developed regions have a more friendly environment for support.

A different way is to use the spatial approach. Ramajo et al. (2008) develop a spatial regression framework using data for a set of European regions. This model produces a couple of results: Firstly, the model shows the existence of (at least) two convergence clubs based on GDP per capita. Secondly, it confirms the initial hypothesis that there are spatial spillovers and effects in this setting. For instance, regions from different clubs will compete, thus, hindering growth. In general, the findings agree with the works of other authors.

Calegari et al. (2021) consider two policies of the EU: Cohesion and Common Agriculture (CAP) Policies. They use data for 2006–2014 on EU regions and apply the β-convergence model. The novelty comes from the inclusion of interaction between policies and exploring structural instability via the threshold autoregression approach. The authors show that both policies positively affect productivity growth only in developed regions. However, less developed regions may profit from both policies. Moreover, the effects of policies vary due to the structural heterogeneity of regions.

In this thesis, I attempt to contribute to the growing field of literature on the convergence of European regions. I study GDP per capita growth and convergence in EU regions in 2000 – 2018. I use two approaches to quantify convergence: variation-based (following Cappelen et al. 2003) and regression-based (following Fagerberg and Verspagen 1996). Using the first approach, I find that log GDP per capita dispersion in EU regions increases overall, but decreases within country. I interpret increases as indicating overall divergence, and decreases as indicating within-country convergence. Using the second approach, I find overall convergence on the full sample. On the stable and top 5 sub-samples, I do not find convergence during the last two programming periods. I include regional characteristics and use modeled real expenditures under EU structural funds as the measure of EU support. Convergence results is robust to these additions. I do not find strong support for the efficiency of EU support.

This paper is organized as follows: Section 2 reviews the main definitions and history of relevant research. Section 3 describes the proposed model and shows variance and regression analyses. Section 4 presents the effects of regional characteristics. Section 5 shows the effect of EU Regional Policy. Section 5 reviews possibilities for further research. Section 6 concludes.

2. Impact of the Cohesion Policy on GDP Growth and Convergence

In this section, I describe EU policies and papers that are relevant for my thesis. I briefly present main elements of the EU policies that are aimed at promoting growth and convergence in EU member states. I write about papers that concentrate on the study of GDP growth and convergence in the EU. The described papers cover different time periods and apply different strategies to research the issue of convergence in the EU. Moreover, I describe studies that comment on the efficiency of the EU Regional Policy.

GDP growth is significant for contemporary life (Rodríguez-Pose 2013). It affects quality of life and is an indicator of the development of any geopolitical unit (for instance, a country or a city). Thus, many researchers study GDP growth. They employ various strategies and apply them to a variety of contexts. For instance, there is a growing set of papers that study the case of GDP growth and convergence (later β-convergence) in the European Union (for example, Fagerberg and Verspagen 1996; Cappelen et al. 2003; Ramajo et al. 2008). I aim to contribute to this field of research. These articles concentrate on a broad sample of European countries and use similar empirical strategies. Some similar features are (1) usage of country fixed effects (country F.E.) and (2) interpretation of results in terms of convergence clubs – a group of countries/regions that have similar characteristics and show similar growth patterns (Fagerberg and Verspagen 1996). An alternative approach is to develop a theoretical model that motivates empirical model and estimation (for instance, Sterlacchini 2008).

2.1 Purpose and Description of the EU Cohesion Policy

Regional policy (RP) is one of the main instruments of the EU to promote the cohesion of regions. Making regions uniform in terms of their development has been recognized formally as one of the main targets of the EU since the beginning (European Community, 1987, as cited in Calegari et al. 2021, p. 28). The Cohesion Policy (CP) became even more critical with new countries entering the EU. Thus, the heterogeneity of members regarding a variety of indicators increased. Additionally, the CP was needed to support weaker members as they faced competition from more developed countries in the European Single Market. The European Commission (2021) indicates that €461 bio. was invested under CP schemes in 2014–2020.

The European Commission (2022a) indicates that CP is one of the most important policies of the EU. Cohesion Policy consists of several elements:

1. Cohesion Fund (CF);
2. European Regional Development Fund (ERDF);
3. European Social Fund (ESF);
4. Just Transition Fund (JTF).

The European Commission (2022b) states that CF will provide financing to states with Gross National Income (GNI) per inhabitant below 90% of the EU-27 average for the 2021-2027 programming period. For the 2014-2020 period, eligibility was defined relatively to EU average GNI. The same rule applied to the 2007-2013 and 2000-2006 programming periods.

The Cohesion Policy works at the regional level defined by the NUTS classification. NUTS stands for "Nomenclature of Territorial Units for Statistics" (Eurostat 2021)and was developed by

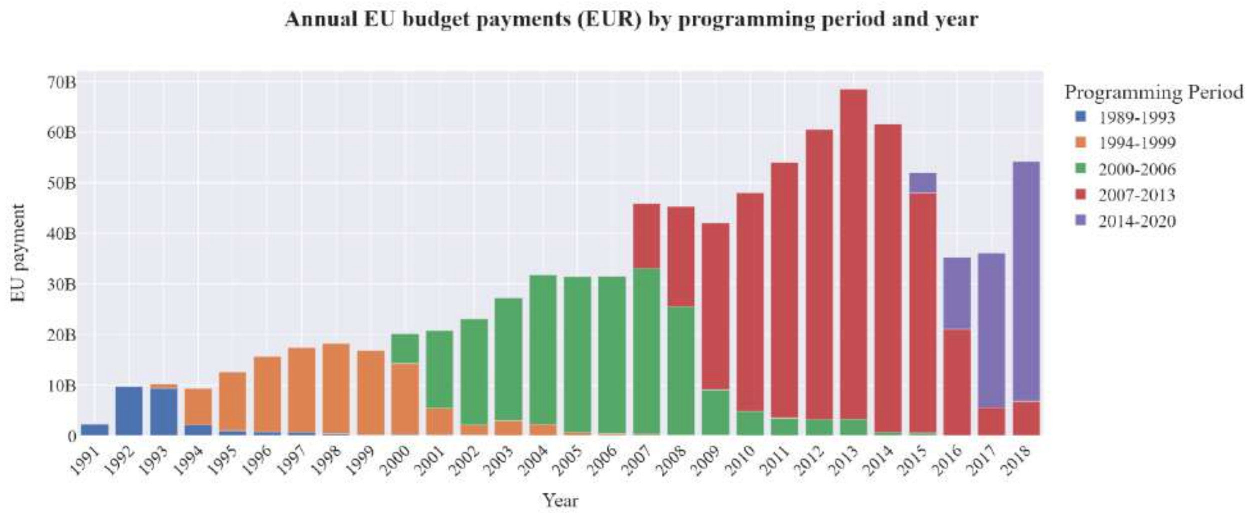

Figure 1. Annual payments under various EU support funds and for different programming periods summed by year. Payments under ERDF, CF, ESF, and EAFRD are accounted for. Source: Author's calculations

Eurostat. NUTS levels differ in terms of population. Objectives are defined at the NUTS2 level – from 800 000 to 3 Mio. people.

Financially, the Cohesion Policy consists of transfers from Structural Funds (SFs). Transfers under the CP target regions that are eligible for financing. There is a set of such criteria or objectives. The most relevant criterium for eligibility is Objective 1 (or Cohesion Objective). All objective 1 regions have GDP per capita in purchasing power standards (PPS) below 75% of the EU average (Cappelen et al. 2003). Additional examples of objectives are Objective 2 which is aimed at regions in industrial decline (measured by simultaneously high unemployment and low employment growth rates) and Objective 5b which targets agricultural regions (defined via a share of agricultural employment and per capita GDP). The ERDF and CF promote development, cohesion, and innovations in regions. The ESF and JTF aim at green development and transition to a sustainable economy. While these programs have different targets, they have a unified regulation system.

Overall, Figure 1 shows increasing trend in annual payments under various EU support funds. This graph sums payments made under European Regional Development Fund (ERDF), Cohesion Fund (CF), European Social Fund (ESF), and European Agricultural Fund for Rural Development (EAFRD). Moreover, Eurostat (2021) indicates that even more demand for the Cohesion Policy is expected later.

2.2 Review of Research on the Cohesion Policy and GDP Convergence in Europe

A diverse set of papers studies the effects of the CP. The researchers review different periods, disaggregation levels, and econometric techniques. Thus, there is heterogeneity in the results obtained. Cappelen et al. (2003) find overall positive results of the CP on GDP growth and convergence. However, Fagerberg and Verspagen (1996) find that the CP has a negative effect in regions with high unemployment. Moreover, Calegari et al. (2021) provide evidence that relatively less developed regions are harmed by the CP.

Sala-i-Martin (1996) is the first to study the issue of convergence in the EU. Sala-i-Martin documents convergence in multiple countries, including EU members (Germany, France, Italy, the UK, and Spain) US, and Japan. The author shows that the convergence pattern is not different across the studied entities. Thus, Sala-i-Martin (1996) provides evidence of the inefficiency of EU Regional Policy.

Fagerberg and Verspagen (1996) study GDP growth and convergence of European regions in the post-war period. They emphasize that European policy targeted convergence in macro variables, including inflation, and public account deficit. However, they show that convergence in these characteristics does not necessarily lead to convergence in incomes or quality of life.

Fagerberg and Verspagen (1996) base their research on Schumpeterian perspectives on technologies rather than neoclassical growth theory. They claim that the technological gaps approach brings a better fit to the real world. Thus, the authors highlight the importance of technological diffusion and innovations in reducing regional disparities.

The authors use a sample of 70 regions from six EU member states. Specifically, they include the UK, Netherlands, Belgium, France, Germany, and Italy. Their primary variable of interest is GDP per capita in a given region. Fagerberg and Verspagen use data on investments, employment, and transfers under the European Cohesion policy.

Fagerberg and Verspagen (1996) show that there is evidence in favor of strong convergence of European regions before 1970. The average difference in growth rates between the poorest and the wealthiest regions was about 4.3%. However, they estimate that convergence became weaker later. The average difference was approximately 2.4% in 1970-1990. Moreover, there is no evidence of a catch-up in GDP per capita terms in the 1980s. It means that the gap between poor and rich regions did not diminish.

Seeking to explain the diverging trend in investments, Fagerberg and Verspagen (1996) include different measures of investment outputs, inputs, and support from the EU in the form of investment loans. Their estimates show that R&D has a positive effect on regional convergence. Investment loans also have a positive impact, but the authors suggest that loans are not randomly distributed. Hence, Fagerberg and Verspagen (1996) highlight possible reverse causality in the case of investment loans from the EU. Thus, investments play a significant role in promoting convergence at the regional level.

Fagerberg and Verspagen (1996) study the heterogeneity of regions further. They apply clustering to the sample and find three convergence clubs. Under convergence club they mean a group of regions with similar characteristics. Thus, they find evidence in favor of European regions converging differently. Significantly, the effects of EU support and investments vary across the clubs. These effects are significant and positive only for regions with low unemployment.

Fagerberg and Verspagen (1996) find varying support for the existence of convergence in Europe. While the EU regions converged before 1980, this trend later changed. However, they argue that innovations and EU support can be helpful in fostering cohesion. In their opinion, the critical point is that the effectiveness of innovations and support depends on the characteristics of a region.

Fagerberg, Verspagen, and Caniëls (1997) study GDP growth in the EU regions. The new paper adds to Fagerberg and Verspagen (1996) by taking employment dynamics and migration into consideration. The authors use data on the EU regions in 1980s. Fagerberg, Verspagen, and Caniëls use instrumental variables in their paper. The main reason behind this is that GDP growth, migration, and employment are interdependent. However, instrumental variables can solve this issue. The authors show that the EU might suffer from the trap of high unemployment and low GDP per capita. This finding is consistent with the convergence clubs from Fagerberg and Verspagen (1996). The channel is as follows: Unemployment decreases migration into a region and increases migration from region. Simultaneously, net migration inflow has a positive effect on GDP per capita growth.

Fagerberg, Verspagen, and Caniëls (1997) provide policy recommendations in light of their findings. For instance, R&D increase in poor regions might improve the situation. However, this policy is complicated and requires not only funding but also infrastructure. Moreover, the effect of R&D is long-run, or structural. Thirdly, economic structure change (decrease of agriculture in poor regions) might as well change GDP per capita growth in poor regions.

Boldrin and Canova (2001) study regional GDP growth and convergence in EU15 countries. Boldrin and Canova concentrate on the effect of Structural Funds on the growth of regions. The authors show no evidence in favor of either divergence or convergence in the EU in 1986 – 1996. Boldrin and Canova (2001) conclude that EU regional policy is mostly redistributive and does not promote economic growth.

Fagerberg and Verspagen (2002) continue with studies of innovations and economic growth. However, in this paper, the authors apply evolutionary framework. The authors stress the importance of technological progress as well. Overall, Fagerberg and Verspagen (2002) indicate that economies change over time. They switch between periods of convergence and divergence. Fagerberg and Verspagen (2002) underline the special case of the USA that diverges from the rest of the world based on the data for 1990s. The authors stress the importance of innovations. Innovations are relatively more important factor for explaining growth differences now.

Cappelen et al. (2003) study GDP per capita growth and convergence. They concentrate on the 1980s–1990s and the reform of EU regional policy. Their focus is the direct estimation of the long-run effects of the European Cohesion Policy. Cappelen et al. (2003) enhance the approach of Fagerberg and Verspagen (1996). While Cappelen et al. still use a set of factors that influence growth, they concentrate primarily on regional support under structural funds. The authors propose a new estimation procedure that combines spatial and temporal variations to identify the effect of support from the EU. Specifically, the authors account for spatial variation by including country dummies. The authors account for temporal variation by including time dummies and interactions between time dummies and explanatory variables.

Cappelen et al. (2003) study a set of European regions from 1980 to 1997. They use regional divisions on NUTS1 and NUTS2 levels. The authors examine countries that were in the

EU before the 1990s, and account for regional support aimed at lagging regions, regions in industrial decline, and rural and agricultural regions. Moreover, they use data on employment, infrastructure, population density, and R&D personnel. The authors show that there is mixed evidence in favor of regional convergence. While the variation of GDP per capita decreases in the whole sample, there is divergence if Greece, Portugal, and Spain are excluded. Moreover, variation inside countries is almost the same for different years and samples. Thus, Cappelen et al. (2003) conclude that there was no increase in convergence in the EU during the period of time studied.

Cappelen et al. (2003) use clustering to study the division of the sample. They find four interpretable clusters in comparison to three convergence clubs in Fagerberg and Verspagen (1996). Largely, the division is explained by the specialization of regions: R&D, manufacturing, or agriculture. As different clusters attract support under different objectives, the authors claim that the actual distribution of funds is tightly connected to the objectives of the CP.

Cappelen et al. (2003) use a version of the β-convergence model similar to Fagerberg and Verspagen (1996) in both specification and used variables. They evidence that the European support policy has a positive impact on regional growth and catch-up. The authors emphasize that positive influence of support policy on regional convergence could be a result of the European reform of support funds. However, there are also some questions arising from this analysis. One of the most critical issues is related to the low effectiveness of support in less developed regions that are less receptive to the support. Another issue is that less developed regions are significantly limited by low R&D and a high share of agriculture in industry.

Overall, Cappelen et al. (2003) show that EU policy has a positive and significant impact on GDP growth and the convergence of EU regions. However, their crucial point is that less developed regions cannot fully use the support provided. Thus, they claim that effective policy should provide financial support and promote the quality of local governments.

Ramajo et al. (2008) also study GDP growth and convergence in EU regions. They investigate the impact of funds created by the EU and aimed at poor regions of EU members. However, they use the spatial regression approach to study interregional spillovers. Overall, Ramajo et al. (2008) work in the same theoretical setting of β -convergence as Fagerberg and Verspagen (1996) and Cappelen et al. (2003). The authors concentrate on the spatial approach to convergence. Thus, they allow spatial externalities in their model. The authors base their modification of the model on the new economic geography and endogenous growth theories. Hence, they underline the value of geography for GDP growth and convergence.

Using data for 1981–1996 from the REGIO database, Ramajo et al. (2008) include 163 regions at the NUTS2 level. The sample consists of countries from the EU12 list, including those from Fagerberg and Verspagen (1996). Their dependent variable is GDP per capita. Additionally, they use data on employment: overall employment level and agricultural employment.

The authors develop a spatial regression framework using data for a set of European regions. This model produces a couple of results: Firstly, analogous to Fagerberg and Verspagen (1996), the model shows the existence of (at least) two convergence clubs based on GDP per capita. Secondly, it confirms the initial hypothesis that there are spatial spillovers and effects in this setting. Ramajo et al. (2008) find evidence of two groups of regions: Cohesion and Non-Cohesion clubs. While the former group experiences stronger convergence of about 5% in terms of GDP per capita, the latter converges at a much lower speed of approximately 3%. As the Cohesion club consists of countries targeted by the CP, the results support the effectiveness of EU policies.

Moreover, the spatial correlation of initial conditions is positive, indicating the existence of positive externalities.

Ramajo et al. provide evidence that supports the Cohesion Policy. Moreover, they find that this policy has a more prominent influence in the less-developed regions. One of the key aspects are positive spatial spillovers. Thus, developed neighbors stir growth in poorer regions. This indicates the importance of coordination between agencies and countries to reinforce cohesion.

Sterlacchini (2008) conducted another study of EU regions, concentrating on the impact of human capital and R&D on GDP growth and convergence. The author argues that while human capital positively correlates with GDP growth, R&D expenditures matter only for sufficiently developed countries. The author finds two groups (northern and southern countries) that differ in the influence of R&D expenses. Sterlacchini conducts the research using a sample of 197 regions of 12 countries from the EU15 list for 1995–2002.

Sterlacchini (2008) uses a more classical approach than Ramajo et al. (2008) that relates to Fagerberg and Verspagen (1996). Sterlacchini (2008) arrives at similar conclusions to Ramajo et al. (2008). However, he divides countries in a different manner than Ramajo et al. (2008) into two groups: northern and southern countries. He shows that R&D is not an important GDP growth factor for southern countries and provides two explanations for this. Firstly, there can be insufficient innovations (R&D expenses) in the southern group, and, secondly, weak institutions may be the cause. Overall, this crucial observation requires more granular study to understand fully.

Dall'erba and le Gallo (2008) study the effect of EU Structural Funds on GDP growth and convergence. The authors use data on 1989 – 1999. Dall'erba and le Gallo (2008) use a spatial econometric toolbox combined with instrumental variables to find that EU regions converged in 1989 – 1999, but EU support did not affect the convergence.

Becker, Egger, and von Ehrlich (2010) study the EU Structural Funds program. The authors apply a Regression Discontinuity Design to research the causality between the EU support and the economic growth of the regions. Becker, Egger, and von Ehrlich (2010) use two outcome variables: GDP growth and employment growth. The authors use Objective 1 transfers as treatment. Becker, Egger, and von Ehrlich (2010) use the assignment rule of Objective 1 transfers for identification. Thus, the authors compare the regions that were just eligible for support to the regions that were close to being eligible to receive the support. Becker, Egger, and von Ehrlich (2010) show that EU support increases GDP per capita growth in treated regions. The authors find that there is no significant effect of EU transfers on employment growth.

Franks et al. (2018) study convergence in the EU among multiple characteristics, including interest and inflation rates, income levels and productivity, and convergence in business and financial cycles. Franks et al. (2018) study convergence in terms of GDP per capita growth and variation. They use data for 1960 – 2015.

Franks et al. (2018) show that EU countries converged in 1960 – 2015. However, the authors argue that the GDP per capita growth convergence slowed down and eventually stopped after the Maastricht Treaty. Franks et al. (2018) indicate that the GDP per capita variation increased after 2010 signaling divergence of EU regions.

Calegari et al. (2021) review the cohesion of the EU regions. However, they use an approach that is different from Cappelen et al. (2003) and Ramajo et al. (2008). Calegari et al. (2021) study the Common Agriculture Policy of the EU and its interaction with the Cohesion Policy. Moreover, they use Gross Value Added (GVA) per worker in agriculture as a dependent variable instead of GDP per capita. Additionally, they show that the effects of the CAP and CP vary with the initial GVA of the region.

Calegari et al. (2021) use data on NUTS2 regions from EU-25 countries with the exception of Bulgaria and Romania. They merge data from the CAP to the sample of EU regions. The authors consider one programming period, from 2007 to 2013, but add one additional year at the start and end of the period to account for more long-term effects of financing and regional dynamics.

Calegari et al. (2021) fit a version of the model used in Fagerberg and Verspagen (1996). The main difference is usage of GVA instead of GDP. This model is further augmented by payments received under the CAP and CP, and interaction of these payments. Moreover, the authors use an approach similar to Threshold Autoregression to analyze whether the effects of payments are stable across different regions. Instead of time, they use initial conditions, GVA per worker in agriculture at time 0, to construct the greed for the search of threshold parameter.

Calegari et al. (2021) conclude that the CAP and CP have different effects. Analogous to Cappelen et al. (2003), while less developed regions are harmed by these policies, more developed regions are able to profit from them. However, the crucial point is that the interaction effect is reverse: in regions with low initial GVA, CAP and CP have a positive interaction effect, but in regions with high initial GVA they have a negative interaction effect.

In this section, I summarized relevant information about the EU Regional Policy. Regional Policy consists of multiple funds that provide financial support for a variety of objectives, including the promotion of GDP growth and convergence in EU regions. I summarize a number of papers that study GDP growth and convergence in the EU in different periods and use different empirical approaches. While some authors conclude that EU policies are unsuccessful (Sala-i-

Martin 1996; Boldrin and Canova 2001; Dall'erba and le Gallo 2008), other authors provide evidence that Regional Policy has positive impact on GDP growth and convergence (Cappelen et al. 2003; Ramajo et al. 2008).

3. Estimating the Effect of the Cohesion Policy

In this section, I describe my study of GDP growth and convergence in the EU in 2000 – 2018. I begin with the description of my sample and the presentation of descriptive statistics. Then, I show the results of preliminary analysis of GDP per capita variance in EU regions. I estimate β-convergence model and compare regression results with the results obtained from the analysis of variance. Then, I analyze sub-samples of data and provide visual evidence to reconcile the results of regression and variance analyzes.

3.1 Sample of European Regions

My initial aim was to recreate the study by Fagerberg and Verspagen (1996) and expand it in the time dimension from 1990 onward. The main issue affecting the possible replication of this study was the scarcity of data. Fagerberg and Verspagen (1996) use a sample of European regions at the NUTS2 disaggregation level. They have data on 70 regions from six EU countries: Belgium, France, Italy, (West) Germany, the UK, and the Netherlands. The countries differ in the number of regions included. While France has 22 regions included (the maximum number of regions for a country), Belgium has just three (the minimal number). The authors use multiple data sources to access needed data. The primary source is Eurostat. However, the authors augment the data from Eurostat with data on the number of R&D projects from the CORDIS database and earlier data on GDP from Molle (1980, as cited in Fagerberg and Verspagen (1996, p. 446)) Overall, Fagerberg and Verspagen summarize the data sources and variables used in Appendix B (p. 447).

However, I encountered multiple problems trying to replicate the study by Fagerberg and Verspagen (1996). The data used by Fagerberg and Verspagen (1996) are currently unavailable at least at their original sources. Thus, I decided to concentrate on the EU after 2000. I use data for 2000 – 2018 due to the availability of historic EU payments under support programs.

For the analysis, I use the raw variables listed in Table 1. All data, except for the loans of the private sector, are aggregated on the NUTS2 level. The primary data source is Eurostat. However, data for payments from the EU to regions are taken from European Commission.

Figure 2 provides the distribution of the initial log GDP per capita in the sample, which is non-standard. It is multimodal, suggesting that there are multiple clusters of regions with different starting conditions. Relatively more density is located on the left side of the graph. Thus, the initial GDP per capita is more densely distributed than the overall GDP per capita. The second row of Figure 2 illustrates the distribution of the final log GDP per capita in the sample. It shows that the distribution has one mode and poorer regions have a more uniform distribution.

Figure 3 shows the spatial distribution of log GDP per capita in 2000. Overall, the picture indicates that older members of the EU have higher GDP per capita. There is a clear cluster of regions with low levels of developed in the East and the Balkans. However, Greece appears to belong to a more developed group of old EU members. Figure 4 shows the spatial distribution of growth differentials for GDP per capita over 2000–2018. Figure 4 shows that old members of the EU have relatively lower growth rates. At the same time, Eastern regions that belong to new EU members have somewhat higher growth rates. Thus, Figure 4 provides evidence that there was convergence, at least among countries.

Overall, exploratory data analysis shows that regions converged in 2000 – 2018. However, the convergence speed and strength remain unclear. Moreover, it is not clear, whether convergence happened only in new regions, or old EU members converged to each other as well. Performed analysis does not explore year by year changes as well. Thus, it gives no information about convergence in specific programming periods. Additional point is that within-country convergence is overlooked by exploratory analysis as well.

Figure 22 (in Annexes) draws the map of regions from the stable sub-sample. I constructed the stable sub-sample in the following way: I took my full sample that has entry of regions and dropped all rows with omitted values in regressors. Then, I took only those regions that had

Table 1. Description of raw variables.

Name	**Description**	**Units**	**Source**
GDP per capita	Gross Domestic Product per inhabitant	EUR27 Purchasing Power Parity*	nama_10r_2gdp
CF, ERDF, EAFRD, ESF	Payment under the respective fund	EUR, Mio.	European Commission
UNEMP	Share of unemployed for age 15-74	%	lfst_r_lfu3rt
EMP	Employment for ages 15-74	Thousands	lfst_r_lfe2emp
AGREMP	Employment in agriculture for age 15-74	Thousands	lfst_r_lfe2en1; lfst_r_lfe2en2
INDEMP	Employment in industry for age 15-74	Thousands	lfst_r_lfe2en1; lfst_r_lfe2en2
EDUC	Share of people with tertiary education for age 25-64	%	edat_lfse_04
EUI	Consolidated loans of the private sector on a country level	% of GDP	tipspc25

Note: Source contains Eurostat code if applicable, otherwise it contains source for the data.
*Purchasing Power Parity (PPS) is estimated based on the purchasing power of one euro by Eurostat.

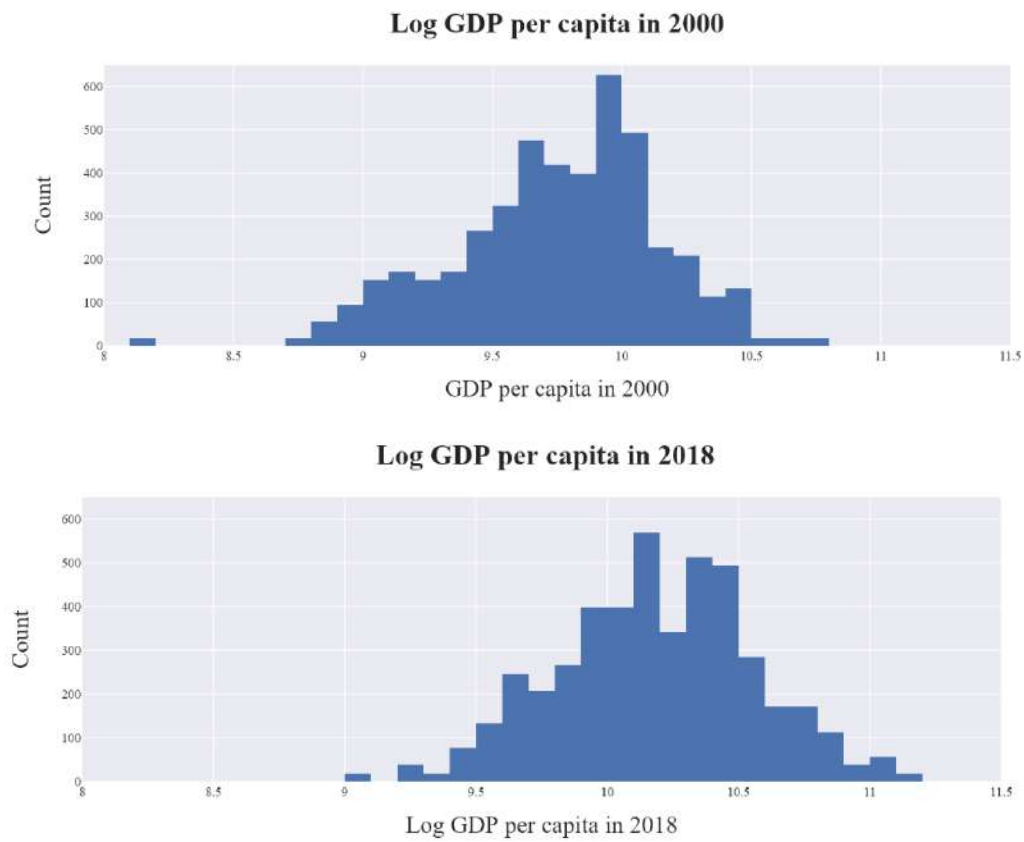

Figure 2. The distribution of GDP per capita in 2000 and 2018 for NUTS2 regions. Source: Author's calculations using data from Eurostat

observations for all years to stable sub-sample.

Figure 23 (in Annexes) shows growth rates for the stable sub-sample. As in the case of full sample, the growth concentrates on the boundaries of the sub-sample. Thus, regions with low levels of development in 2000 have had higher growth rates during 2000 – 2018.

3.2. Summary Statistics for Regional Data

In my analysis, I work with three programming periods that were described before. Additionally, I use data pooled across the periods to provide an additional comparison of results.

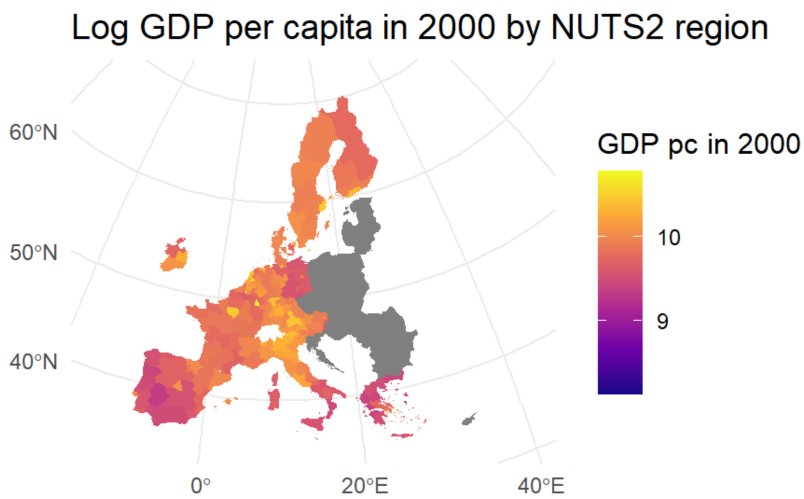

Figure 3. Map of GDP per capita of NUTS2 regions in 2000. Source: Author's calculations using data from Eurostat

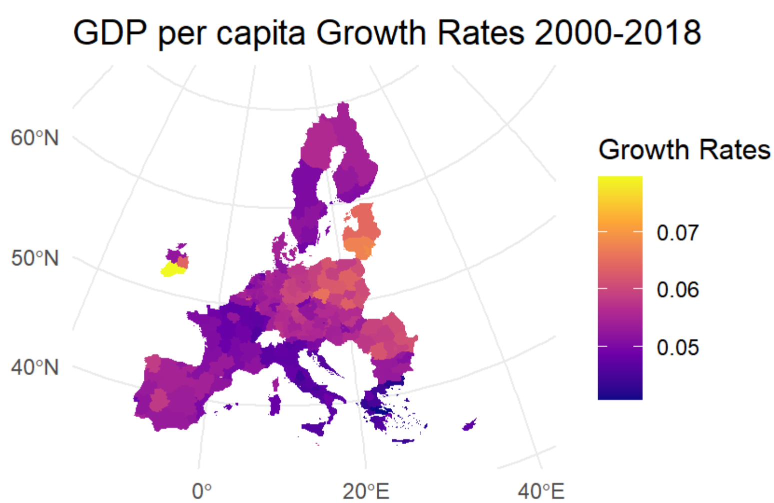

Figure 4. Map of growth differentials of GDP per capita of NUTS2 regions in 2000–2018. Source: Author's calculations using data from Eurostat

Table 2 provides summary statistics for all variables in 2000 – 2018. It summarizes variables from pooled, or full, sample that has 4522 observations but is unbalanced.

GDP per capita has skewed distribution (mean is slightly lower than the median). It shows relatively high variation with standard deviation equal to 0.4. Moreover, range between minimal and maximal values is about 3.

Table 2. Summary statistics, full sample. Source: Author's calculations

Variable	Mean	Median	S.D.	Min	Max
Log GDP per capita	10.0167	10.0345	0.3869	8.1315	11.1676
– in 2000	9.7497	9.7813	0.3967	8.1315	10.7748
– in 2018	10.1842	10.1849	0.3789	9.036	11.1676
CF	5.5113	5.7739	1.6248	0	8.5476
EAFRD	4.6739	5.0454	1.8501	0	8.1415
ERDF	5.4615	5.4471	1.7507	0	9.7577
ESF	5.1981	5.2794	1.2535	0.2094	8.4331
AGR	0.0689	0.0398	0.0808	0.0011	0.5979
IND	0.2235	0.2191	0.0904	0.0241	0.4777
EDU	23.6427	23.1	9.1051	3.6	58.4
g	0.0534	0.0535	0.0055	0.0407	0.0797
g_{log}	0.4344	0.4408	0.1539	0.0507	1.0902

GDP per capita in 2000 is also not symmetrical: Mean is about 0.04 less than median. Standard deviation is higher than in the pooled GDP per capita case. Min-max range is about 2.6. GDP per capita in 2018 is, on contrary, symmetrical. Standard deviation is less than in the pooled GDP per capita. Overall, decreased standard deviation in 2018 can evidence that there was convergence of regions.

I use modeled real expenditures under different EU support schemes from European Commission. I use payments made under CF, ERDF, EAFRD, and ESF. Figure 31 to Figure 34 (in Annexes) show histograms of modeled real expenditures over 2000 – 2018. Figure 29 (in Annexes) shows total expenditures.

Share of agricultural employment (AGR) has, as other variables, skewed distribution. Standard deviation (0.08) is slightly higher than mean value. Maximal value differs significantly from minimal (difference of about 0.6) value. Histograms of AGR for each year can be found in Figure 27 (in Annexes).

Share of industrial employment (IND) has about symmetrical distribution (mean is approximately equal to median). Standard deviation is about the half of mean value. Maximal value is big (0.47) with range equal to about 0.45. Histograms of IND for each year can be found in Figure 30 (in Annexes).

Share of people with tertiary education (EDU) is relatively symmetric. Standard deviation is approximately equal to the half of mean and/or median. Range between minimal and maximal value is, however, big (about 54). Histograms of EDU for each year can be found in Figure 28 (in Annexes).

I use two measures of growth. $g_{\log}$ is logarithmic growth rate. It has skewed distribution with sizeable variance. Moreover, the difference between minimal and maximal values is big – 1.04. g is compound growth rate. It has more symmetrical distribution than log growth. Standard deviation is small compared to mean. However, maximum is still about two times bigger than minimum.

Figure 24 (in Annexes) draws correlation plot for all continuous variables in my full sample. Overall, this figure suggests what can be expected in the empirical part. Growth rates, both compound and logarithmic, are negatively correlated with GDP per capita in 2000. However, other covariates are positively associated with growth rates.

This result is logical for some variables including expenditures under various Cohesion Policy payments and industrial employment. However, agricultural employment has positive weak correlation. I associate this number with the effect of other variables connected to agriculture as well. Overall, I expect negative connection between agricultural employment and growth rates.

Figure 25 (in Annexes) applies the same method to the stable sub-sample. Notably, correlation matrix differs from the full sample case. Firstly, agriculture is now negatively associated with growth rates. Secondly, correlations in stable sub-sample suggest divergence as initial GDP per capita is positively correlate to growth rates. Moreover, these correlation coefficients indicate that the EU policy might be effective as expenditures under the EU support programs have relatively high correlation coefficients with growth rates.

Figure 26 (in Annexes) shows correlation matrix for the sub-sample of five biggest countries. These countries are Germany, Greece, Spain, France, and Italy. I have constructed this sub-sample based on stable sub-sample. I reached this exact list of countries by counting the number of regions in the stable sub-sample and sorting countries in the descending order. On top 5 sub-sample, correlations suggest less efficient policy making by the EU: correlation between expenditures and growth rates is positive and higher than for the full sample. Moreover, investment loans have negative correlation as well. However, growth rates are negatively associated with agricultural employment. Interestingly, correlation between GDP per capita in 2000 and growth rates indicates divergence on this sub-sample as well.

3.3 Preliminary Estimates of GDP Convergence and Divergence in the EU

The EU consists of many countries that differ substantially in their wealth and development. However, one of the EU's priorities is to achieve homogeneity of its constituent members. Thus, the regions of member countries should, in theory, become more similar. If it is true, then convergence is present among EU regions.

However, regions differ in their initial conditions, including initial development, incomes, and natural resources. Moreover, they differ with respect to the efficiency with which they use their endowment. Thus, in the real world, some advanced and efficient regions are likely to profit more from being part of the EU than other regions.

3.3.1 Visual Evidence of Convergence and Divergence in the EU

Figure 5 shows the distribution of log GDP per capita in two years: 2000 (upper) and 2018 (lower). The figure colors bars depending on country. I highlight countries from top 5 sub-sample. These countries are Germany, Greece, Spain, France, and Italy. In 2000, overall distribution is denser than in 2018. However, highlighted countries tend to spread more in 2000 than in 2018. For instance, Germany forms one cluster in 2018 but not in 2000. Spain has denser distribution in 2018 as well as Germany. Thus, Figure 5 shows two potential trends. Firstly, overall distribution became more spread in 2018 than it was in 2000 (overall divergence). Secondly, individual countries have denser distribution of GDP per capita in 2018 than in 2000 (convergence for regions within individual countries).

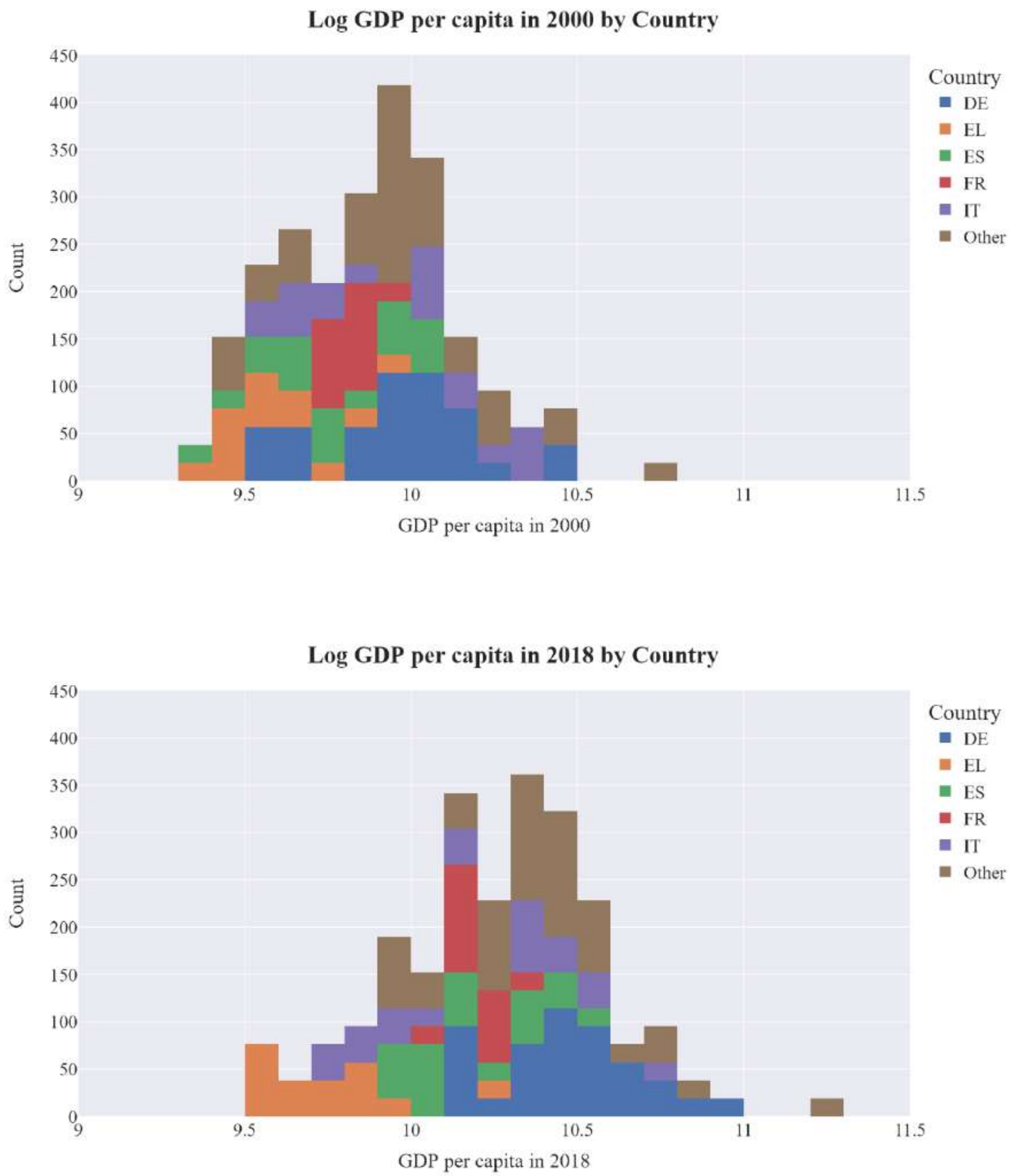

Figure 5. Distribution of regional log GDP per capita in 2000 and 2008 by country in stable sub-sample. Countries from top 5 sub-sample are highlighted. Source: Author's calculations

3.3.2 Variance Decomposition of regional GDP per capita

I follow the approach of Cappelen et al. (2003) to determine whether a diverging or converging tendency is more pronounced in the EU in 2000 – 2018. Cappelen et al. use log GDP per capita variation as the measure of income dispersion in the EU. They apply two different estimation approaches:

1. Regional variation calculated for each year as $var(\log(\frac{GDPpc_i}{\overline{GDPpc_{EU}}}))$, standard deviation of log of GDP per capita of region i relative to the EU average GDP per capita in the same year;
2. Variation within countries calculated for each year as $var(\log(\frac{GDPpc_i}{\overline{GDPpc_C}}))$, standard deviation of log of GDP per capita of region i relative to country C's average GDP per capita.

However, I decompose total variance into two parts:

$$var_t = var_{between_t} + var_{within_t}, \tag{1}$$

where $between_t$ is variance between countries at time t computed as $var(\log(\frac{\overline{GDPpc_C}}{\overline{GDPpc_{EU}}})$, $within_t^i$ is variation within countries from Cappelen et al. (2003).

This approach is relatively simple but can give insights into the convergence of EU regions. Moreover, the within-country measure controls for country difference and is thus net of country convergence. Table 3 shows these two measures applied to my sample.

Full sample includes expansions of the EU. For instance, its' dispersion measure would increase in 2004 due to entry of new EU members. Thus, I use adjustment to solve this problem and make all measures comparable.

Table 3. Variance decomposition by year. Source: Author's calculations

Year	**2000**	**2007**	**2014**	**2018**
Full sample				
Between	0.0789	0.0721	0.0902	0.1269
Within	0.0692	0.0661	0.0545	0.0541
Total	0.1481	0.1382	0.1447	0.1810
Stable sub-sample				
Between	0.0887	0.0975	0.1324	0.1251
Within	0.0428	0.0367	0.0377	0.0367
Total	0.1316	0.1342	0.1701	0.1618
Top 5 sub-sample				
Between	0.0256	0.0135	0.0532	0.0668
Within	0.0482	0.0408	0.0431	0.0419
Total	0.0739	0.0544	0.0963	0.1087

Note: All estimates are multiplied by 100 for readability. Total is sum of Between and Within for respective year. I used log GDP per capita for all computations.

I estimate the variance of GDP per capita each year t as

$$var_t = var_t^e + var_t^n, \tag{2}$$

where var_t^e is variance of GDP per capita in year t in regions that are in the sample since 2000, var_t^n variance of GDP per capita in year t in regions that enter the sample later. I apply the following adjustment:

$$\overline{var_t} = var_t^e + var_t^n - var_a^n, \tag{3}$$

where var_a^n is the variance of GDP per capita in the new regions in the first year they were present in the sample. I use the same principle of adjustment for both between and within estimators.

Overall, Table 3 indicates that regions diverged over 2000 – 2018 as total variance in full sample went up from 0.1481 to 0.1810. However, it was not a monotonous process, as variance in 2007 (0.1382) is smaller than variance in 2000 (0.1481).

Between-country variance show the same pattern as total variance. It increases from 0.0789 in 2000 to 0.1269 in 2018. The two middle values are 0.0721 and 0.0902 indicating convergence in 2000 – 2007. Within-country variance decreases in 2000 – 2018. This process is monotonous. In absolute terms, within-country variance decreases from 0.0692 in 2000 to 0.0541 in 2018.

Stable sub-sample is different to the full sample in terms of variance patterns. Total variance increases from 2000 to 2014 and decreases in 2014 – 2018. Thus, regions from stable sub-sample actually converge during the last four years. Between variance in stable sub-sample follows the same pattern, increasing in 2000 – 2014 and decreasing later. However, within variance, similarly to full sample, overall decreases. It is not monotonous process as between variance in 2014 (0.0377) is higher than in 2007 (0.0367).

Total variance in top 5 sub-sample is similar to full sample case. Initial decrease is followed by increase in 2007 – 2014. Overall, the total variance in top 5 countries increased from 0.0739 to 0.1087. Between variance in top 5 sub-sample follows the total variance. Between variance decreases in 2000 – 2007 and increases afterwards. Within variance in top 5 sub-sample decreases initially and increases afterwards. However, it also decreases in 2014 – 2018.

Figure 6 plots between-country, within-country, and total variance for full sample in 2000 – 2018. All series are adjusted for entry, but not multiplied by 100 (contrary to the values in Table 3). Overall, between-country variance tends to increase in 2000 – 2018. However, it shows downward sloping trend in 2000 – 2004. Between-country variance also shows humps in 2004, 2008 – 2009, and 2012 – 2013. Within-country variance levels off in 2000 – 2007. Later, it increases until 2011. 2011 is the only year in which within-country variance is higher than between

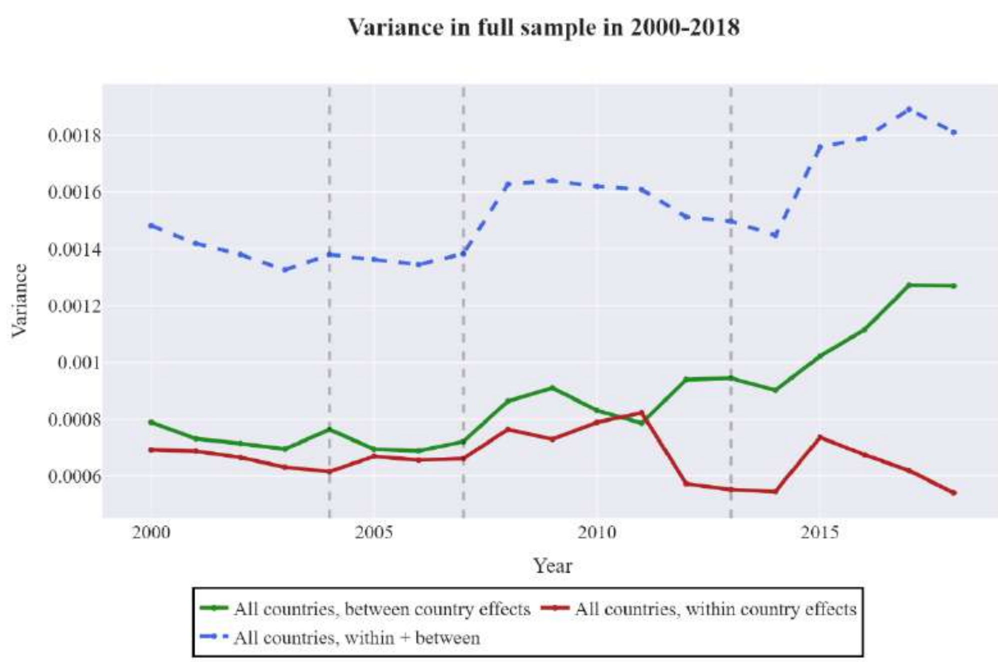

Figure 6. Between-, within-country, and total variance for full sample by year. All series are adjusted for entry. Values are 100 times smaller if compared to Table 3. Dashed lines mark years of entry of new members. Source: Author's calculations

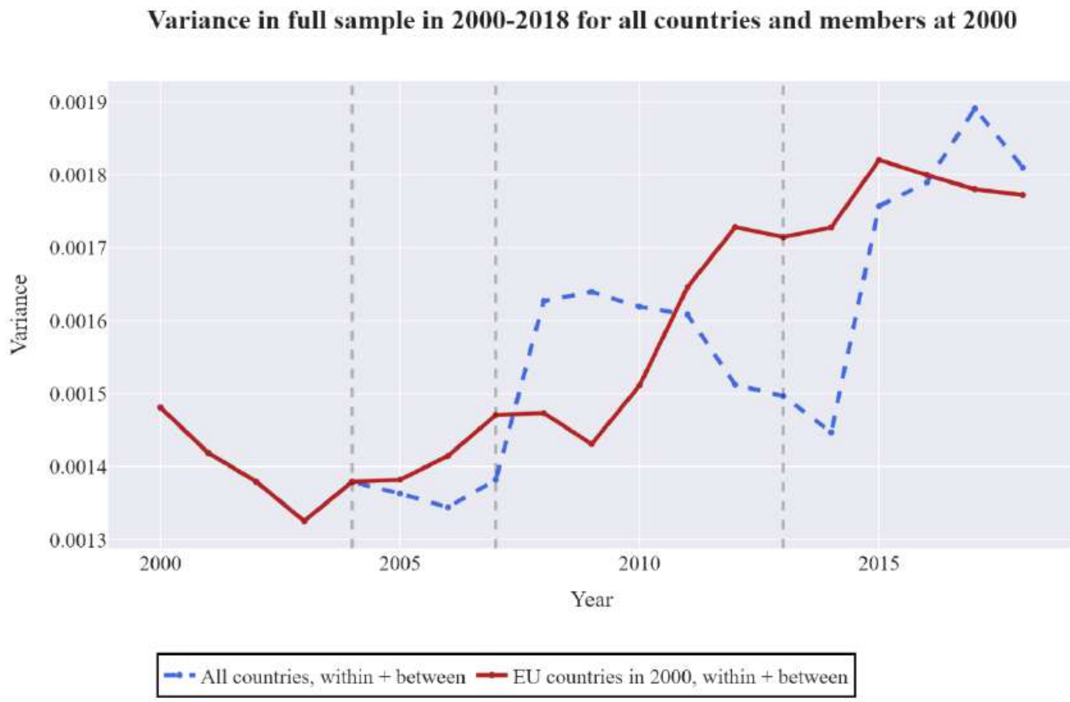

Figure 7. Total variance in full sample. Blue line - series adjusted for entry. Yellow line - series of countries that were in the EU in 2000. Source: Author's calculations

country variance. In 2011 – 2018, within-country variance decreases with downfall in 2012 – 2013.

Figure 7 shows total variance for two cases. Firstly, it shows total variance for all countries. In this case, the values are adjusted for entry of new countries and regions. Secondly, it shows total variance only for countries that were in the EU in 2000. In this case, no adjustment is applied. Total variance adjusted for entry (blue line) follows general trend of total variance of EU members in 2000. However, blue line shows higher variability (more pronounced rises and falls, for instance in 2007 – 2008, 2014 – 2015). Overall, two lines do not converge to each other after 2004.

Figure 8 plots within-country variation lines that summed up give approximately the variance "pit." These countries are Ireland, Bulgaria, Hungary, Romania, Lithuania, and Finland. Notably, only Ireland and Finland are old EU members. Romania recovery from the financial crisis of 2008 (Anonymous 2013) accounts graphically for the fall to the "pit." Ireland's economic fall

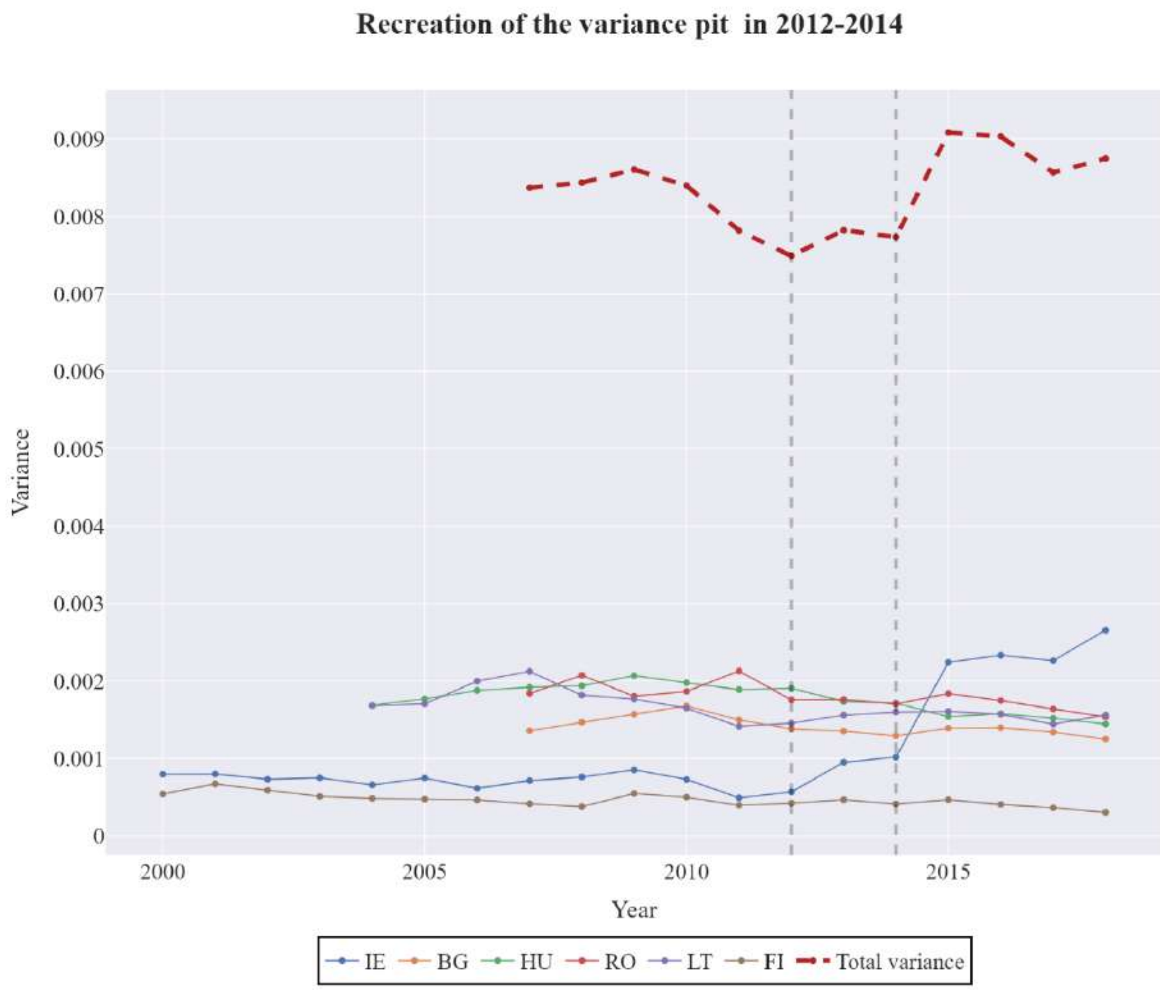

Figure 8. Recreation of variance "pit" in 2012 - 2014 with a subset of countries using within-country variance. Source: Author's calculations

after the crisis (Dabrowski 2010) accounts for the exit from the "pit." Thus, financial crisis of 2008 causes the variance "pit" in the following way. By damaging country economies, financial crisis has two effects. Firstly, it decreases variation due to wealthy regions losing GDP per capita especially in developed regions that were dependent on global financial markets. Secondly, recovery from the crisis causes increase in variation to previous levels.

Overall, a preliminary study of GDP per capita convergence and divergence shows ambiguous results. If I do not use control for country average log GDP per capita, estimates show divergence in the long run. Between-country variance increases in full sample and both sub-samples. Thus, differences between individual countries are more pronounced in the EU now than 20 years ago. The results show that the effect of new countries on regional convergence is about zero over 2000 – 2018. Within-country variance was stable before 2007 and decreased after 2011 if the “pit” is not taken into account. Thus, I show that regional divergence in the EU is largely the result of country divergence.

I show graphical evidence supporting simultaneous convergence and divergence in Figures 6 and 7. My analysis of variation generally agrees with Cappelen et al. (2003). However, there are important differences. Firstly, variation in my analysis shows changes stronger than in Cappelen et al. (2003). Secondly, I estimate overall divergence while Cappelen et al. (2003) shows convergence. Thirdly, my analysis supports within-country convergence in long run (the last value of within-country variance is lower than the first one). Cappelen et al. (2003) does not find evidence of within-country convergence. I support the results of Franks et al. (2018) regarding rising GDP per capita variance. I document rise in the overall GDP per capita variation. My results show trajectory similar to Franks et al. (2018).

3.3 Estimates of the Convergence in the EU

I study the results obtained via variation analysis further in the setting of β-convergence regressions. Thus, I can use usual instruments of regression analysis to determine whether regions in the EU converged or diverged in 2000 – 2018. Moreover, regression allows me to introduce more control variables.

3.3.1 Convergence in the Full Sample

I follow the approach of Fagerberg and Verspagen (1996) in measuring the convergence among the European regions. Table 4 provides estimates of the following model:

$$g_i = \alpha + \beta y_{i0} + \epsilon_i, \tag{4}$$

where g_i is the compound growth rate of GDP per capita of region i, y_{i0} is GDP per capita at the start of the programming period. Table 4 uses data from full sample that has entry of regions. Thus, I estimate the model on three sub periods without pooled version. Estimation for each period includes only countries that were present in the sample at the start of the period.

Table 4 shows that EU regions converged overall in 2000 – 2018. As can be seen in Table 4, EU regions converged in 2000 – 2006. Convergence is present in both specifications (without and with country dummies). However, the speed of convergence is only about 0.01% of growth rates. The model without country F.E. explains only about 20% of all variation of the dependent variable. In 2007 – 2013, similar results are shown. The only difference is that the coefficient in the specification with country dummies is not significant. Table 4 shows again similar results for 2014 – 2018. The only issue is that β coefficient in the specification with country dummies is not statistically significant.

Table 4 provides evidence in favor of convergence in the EU during all programming periods. In the majority specifications, the β coefficient is negative and significant. This result suggests that regions converge both overall and within countries. However, variance shows overall divergence. Thus, regression results do not agree with the preliminary analysis of regional variance that shows overall divergence.

Table 4. Convergence in the EU in full sample by programming period. Source: Author's calculations

Period	**Model**	**Cons.**	**log initial GDP per capita**	**N**	**Adj. R2**
2000 – 2006	No F.E.	.2579*** (.0151)	-.0117*** (.0015)	178	.232
	Country F.E.	_	-.0090*** (.0019)		.999
2007 – 2013	No F.E.	.2506*** (.0150)	-.0122*** (.0015)	237	.182
	Country F.E.	_	-.0027 (.0016)		.999
2014 – 2018	No F.E.	.2844*** (.0238)	-.0075** (.0024)	241	.048
	Country F.E.	_	-.0013 (.0020)		.998

* p<0.05, ** p<0.01, *** p<0.001
Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses.

One potential reason for this discrepancy is non-linear relationship between log initial GDP per capita and growth rates. Figure 10 to Figure 12 (in Annexes) show scatter plots with fitted OLS regression line for specification estimated in Table 4. Figures 10 to 12 do not support the existence of non-linear effects.

The other potential reason for discrepancy is the entry of new regions. Table 4 pools regions from all available countries into the same models. Thus, it has entry of new regions between programming periods (for instance, regions that entered the EU in 2004 are present in regressions for 2007 – 2013 and 2014 – 2018). Thus, the comparison of coefficients across models is complicated and should be done with caution. With evidence of divergence, it is helpful to look at the stable sample – regions that are present in all periods. For this purpose, I use two sub-samples: the sub-sample of stable regions and the subs-sample of top 5 countries. I use the first sub-sample of stable regions to study the convergence and divergence on a wider set of regions. Estimation of the model on the second sub-sample of top 5 countries shows convergence and divergence in the old EU countries.

3.3.2 Convergence in the Stable Sub-sample

Table 5 shows estimation results for the same specification on the sub-sample of regions that were in the EU in 2000. Stable sub-sample shows less significant coefficient than the full sample. Interestingly, Table 5 shows positive β coefficients in some cases (2007 – 2013, 2014 – 2018), even though these coefficients are not significant. These results mostly agree with results obtained by the analysis of variation. The most important difference is that Table 5 shows convergence in 2000 – 2018, while Figures 6 and 7 show overall divergence. However, in other periods regression results from Table 5 are similar to the results based on variation, even though the coefficients are not statistically significant. In 2007 – 2013, the coefficient in the specification without country dummies is positive as predicted by increasing trend in Figure 7. The same applies to 2014 – 2018. Table 5 shows negative β coefficients in the specifications with country dummies. This result agrees with overall decrease in within-country variance shown in Figure 6.

Table 5. Convergence in the EU in stable sub-sample by programming period. Source: Author's calculations

Period	Model	Cons.	log initial GDP per capita	N	Adj. R2
2000 – 2018	No F.E.	.0642** (.0216)	-.0012 (.0022)	178	-.000
	Country F.E.	_	-.0052** (.0019)		.996
2000 – 2006	No F.E.	.2597*** (.0151)	-.0117*** (.0015)	178	.232
	Country F.E.	_	-.0090*** (.0019)		.999
2007 – 2013	No F.E.	.0853* (.0371)	.0039 (.0036)	178	.008
	Country F.E.	_	-.0041* (.0020)		.999
2014 – 2018	No F.E.	.1625*** (.0298)	.0042 (.0030)	178	.007
	Country F.E.	_	-.0009 (.0029)		.998

* p<0.05, ** p<0.01, *** p<0.001
Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses.

I check for potential non-linearities in the stable sub-sample. Figure 13 to 17 show scatter plots of compound growth rates (dependent variable) against log initial GDP per capita (independent variable). Scatter plots also show fitted OLS lines for specifications from Table 5. These graphs do not identify any evidence of non-linear relationship.

3.3.3 Convergence in the Top 5 Sub-sample

I re-estimate both of my specifications on the sub-sample of top 5 countries. This procedure checks if my results hold on the most conservative sub-sample. Moreover, this sub-sample includes countries that are old EU members. Thus, they can potentially differ in regional GDP growth and convergence from younger EU members that are present in the full sample.

Table 6 shows the estimation results of both specifications on the top 5 sub-sample. The results are overall similar to the results obtained on the stable sub-sample in Table 5. Table 6 indicates overall convergence in 2000 – 2018. This result contradicts Figures 6 and 7 that show divergence in 2000 – 2018. However, other programming periods generally agree with the results from the preliminary study of regional GDP per capita variance. The same contradictions were present in the stable sub-sample in Table 5. Thus, there are no major differences between top 5 and stable sub-samples in terms of regression results.

I check for non-linear relationship between compound growth rates and log initial GDP per capita in top 5 sub-sample. Figure 18 to 21 present scatter plots with fitted OLS lines for all specifications in Table 6. Scatter plots do not show any evidence of non-linear relationship.

Table 6. Convergence in the EU in top 5 sub-sample by programming period. Source: Author's calculations

Period	**Model**	**Cons.**	**log initial GDP per capita**	**N**	**Adj. R2**
2000 – 2018	No F.E.	.0729** (.0274)	-.0022 (.0028)	118	.010
	Country F.E.	_	-.0063** (.0021)		.997
2000 – 2006	No F.E.	.2919*** (.0180)	-.0151*** (.0018)	118	.318
	Country F.E.	_	-.0104*** (.0021)		.999
2007 – 2013	No F.E.	.0885 (.0526)	.0035 (.0052)	118	-.000
	Country F.E.	_	-.0054* (.0024)		.999
2014 – 2018	No F.E.	.1648*** (.0248)	.0039 (.0024)	118	.026
	Country F.E.	_	-.0023 (.0023)		.999

* p<0.05, ** p<0.01, *** p<0.001

Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses.

In the literature, some papers provide evidence of convergence in the EU (Cappelen et al. 2003; Ramajo et al. 2008). However, Fagerberg and Verspagen (1996) find mixed evidence of convergence using data from the late twentieth century. In their paper, there is no convergence in models with country F.E and there are no positive significant coefficients as well. Thus, I add to their results by showing significant within-country convergence on newer data. My results are in line with Franks (2018). However, I expand studied time dimension by looking at 2016 – 2018.

3.3.4 Reconciling Results from Variance Analysis and Regressions

The results from the preliminary analysis of variance suggest that there is a difference between GDP per capita dynamics on the country and regional level. While regions within countries converge, countries themselves tend to diverge based on Figure 6. Interestingly, regression results on the full sample do not agree with Figure 6. Table 4 shows only convergence overall and within countries. The results are partially reconciled by study of stable and top 5 sub-samples in Tables 5 and 6 respectively. They show convergence within-country and divergence after 2007 as predicted by the variance. However, divergence results are not significant. As variance analysis does not include any measure of statistical significance, Tables 5 and 6 agree with the results from variance analysis. Thus, entry of regions can be the potential cause of the discrepancy between Table 4 and Figure 6.

Figure 9 shows lines for each region that connect log GDP per capita in 2000 and 2018. I show lines for 80 randomly chosen regions from the full sample[1]. Dots without lines show regions that entered the sample after 2000. Figure 9 shows two things. Firstly, log GDP per capita variation

[1] If I plot all available regions, the graph becomes unreadable. However, the picture for all regions shows the same overall results.

in 2018 is partially increased by the entry of new regions as they are relatively more spread than the existing regions in 2018. Secondly, existing regions can be divided into multiple groups based on high or low growth rates (slope of the line for a region) and high or low level of GDP per capita in 2000. Thus, regions that have low initial log GDP per capita but have high growth rates are mixed with regions that have high initial log GDP per capita but have low growth rates. Variation of log GDP per capita in 2018 is additionally increased by regions with low initial log GDP per capita and low growth rates and by regions with high initial log GDP per capita and high growth rates. Thus, while variance describes the whole picture, regression analysis in Table 4 catches the effect of convergence between regions with low initial GDP and high growth rates and regions with high initial GDP and low growth rates.

In this section, I conduct two analyses of regional GDP convergence in the EU. Firstly, I analyze the log GDP per capita variance in 2000 – 2018. I use decomposition into two elements, within- and between-country variance to show that overall divergence is evidently achieved by countries becoming more different. On the contrary, within-country variance decreases in the long run. I use regression analysis to check this result. However, regressions on the full sample support only convergence. I analyze stable and top 5 sub-sample to determine if this discrepancy is caused by the entry of new regions. Moreover, I plot log GDP per capita in 2000 and 2018 for individual regions in Figure 9 to visually inspect possible reasons for the discrepancy. I show that there are two potential reasons. Firstly, new regions tend to increase log GDP per capita variance in 2018. Secondly, there are two groups of regions that potentially drive the regression results. The first group consists of regions with low initial levels of log GDP per capita but high growth rates. The second group consists of regions with high initial levels of log GDP per capita but low growth rates. These two groups blend in 2018 “creating” convergence.

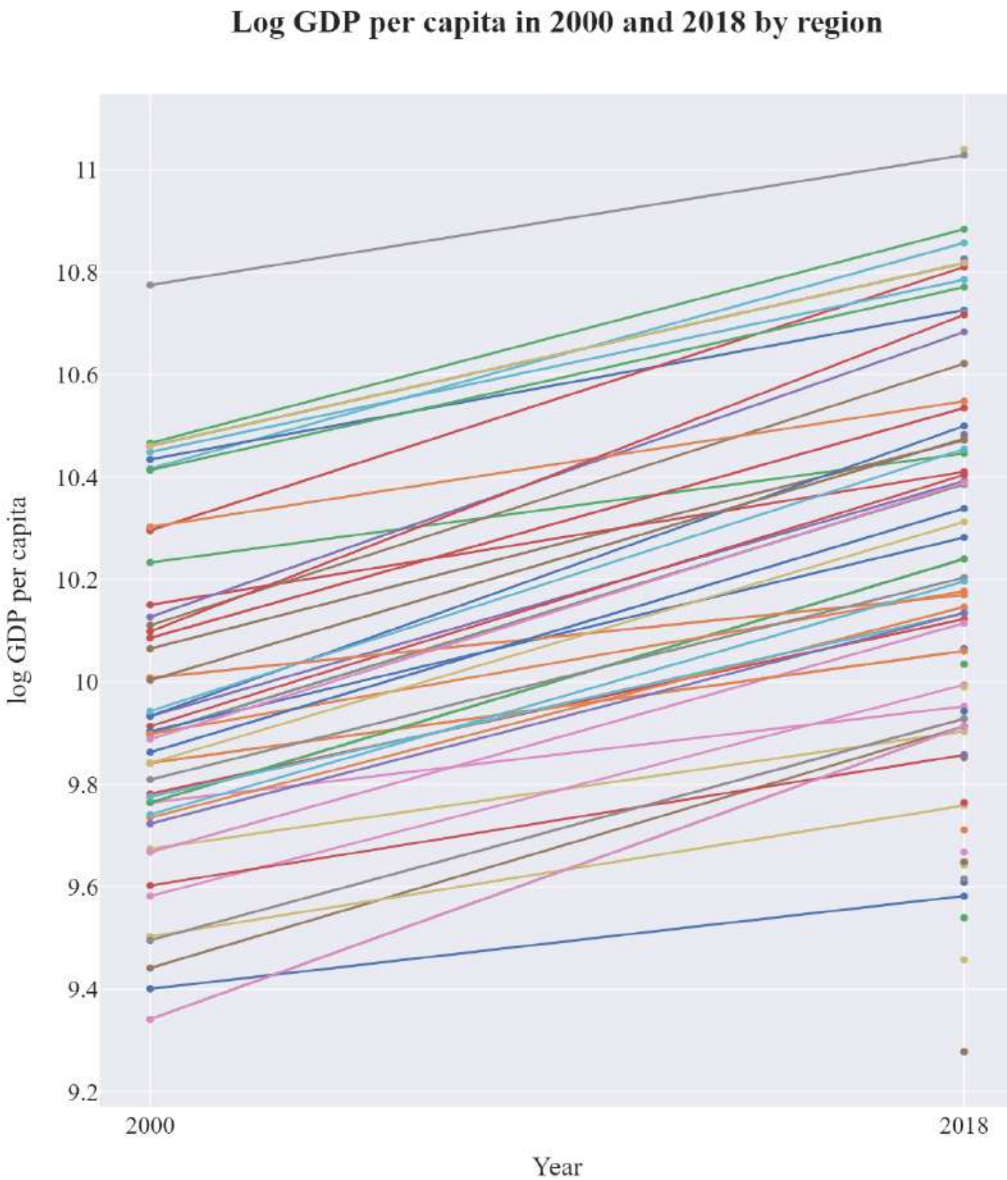

Figure 9. Log GDP per capita in 2000 and 2018 in full sample for 80 regions. Source: Author's calculations

4. The Effect of Regional Characteristics on Convergence

In this section, I study the influence of regional characteristics on the convergence of GDP per capita in the EU in 2000 – 2018. I estimate (4) with added control for regional characteristics, including shares of agricultural and industrial employment and people with tertiary education. I re-estimate my specifications on the full sample and stable and top 5 sub-samples.

4.2 The Effect of Regional Characteristics in Full Sample

The results from the regression tables account for country effects if country dummies are included. However, there are many other factors that influence GDP per capita and growth rates. For instance, unemployment and the share of agriculture are important factors (Fagerberg and Verspagen 1996; Fagerberg, Verspagen, and Caniëls 1997). Thus, I perform an additional estimation of the model from the equation (4). However, I include additional control variables that should account for different regional characteristics, including the support from the EU, the development of industry, and the share of agriculture in the economy of a given region.

Table 7 shows estimation results of the specifications with the gradual inclusion of regional characteristics. The main result about convergence is robust to the inclusion of additional variables. However, there are unexpected results about the effect of some of the regional characteristics. The share of agricultural employment has a positive effect on growth rate unless country and year dummies are included. The share of industrial employment does not have a significant influence in the specification with country and year fixed effects. The share of people with tertiary education

Table 7. Regressions for 2000 - 2006 with additional control variables in full sample. Source: Author's calculations

	(1)	(2)	(3)	(4)
Log GDP pc in 2000	-.0095***	-.0098***	-.0102***	-.0088***
	(.0009)	(.001)	(.0008)	(.0007)
Agricultural employment	.0237***	.0214***	.045***	-.0103*
	(.0041)	(.0043)	(.0048)	(.0053)
Industrial employment		-.0065**	.0039	-.0024
		(.0028)	(.0025)	(.0026)
Education			.4302***	.2021***
			(.0278)	(.037)
Cons	.2362***	.2411***	.2317***	Country and year dummies
	(.0095)	(.0099)	(.0088)	
N	1025	1025	1025	1025
Adj. R2	.2479	.2507	.4021	.9993

* p<0.05, ** p<0.01, *** p<0.001
Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses. Education is divided by 1000 for tractability.

has a positive effect on growth rates in all specifications.

Table 8 shows estimation results of the specification with included country and year dummies for different programming periods. The main result about convergence remains unchanged. Table 8 partially solves the puzzle of the negative effect of the share of industrial employment. In Table 8, the share of industrial employment has a significant positive influence on

Table 8. Regressions with additional control variables in full sample. Source: Author's calculations

Programming period	2000 – 2006	2007 – 2013	2014 – 2018
Log GDP pc in 2000	-.0088***	-.0004	-.0008
	(.0007)	(.0007)	(.0018)
Agricultural employment	-.0103*	.0142***	.0136***
	(.0053)	(.0026)	(.005)
Industrial employment	-.0024	.0072***	.011***
	(.0026)	(.0023)	(.0031)
Education	.2021***	.1643***	.1376**
	(.037)	(.0284)	(.0567)
N	1025	1499	1129
Adj R^2	.9993	.9991	.9987

* p<0.05, ** p<0.01, *** p<0.001

Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses. Country and year F.E. are included. Education is divided by 1000 for tractability.

growth rates after 2000 – 2006. However, the share of agriculture has a positive effect on growth rates in all specifications.

4.3 The Effect of Regional Characteristics in Stable Sub-sample

I re-estimate the specification with country and year dummies included on the stable sub-sample to check the robustness of the results in Tables 7 and 8. Table 9 shows the results of the estimation. The results are similar to Table 8 and keep the result about divergence from Table 5. The only difference is that convergence in 2000 – 2018 is now significant. The puzzle about the positive influence of the share of agricultural employment remains unsolved. Moreover, the share of people with tertiary education loses significance in 2014 – 2018. However, it is most probably associated with a relatively low number of observations for this period. Nevertheless, the coefficient remains positive. Table 12 (in Annexes) presents the estimation results of the same specifications on the top 5 sub-sample. The results remain qualitatively the same if compared both to Tables 6 and 8.

The inclusion of regional characteristics does not change the main results. However, it adds puzzle about the positive influence of agriculture on growth rates. One potential explanation for this feature is endogeneity: Agricultural regions have low levels of GDP per capita and are eligible to receive support from the EU. It increases their growth rates and makes the coefficient positive.

Table 9. Regressions with additional control variables in stable sub-sample. Source: Author's calculations

Programming period	2000 – 2018	2000 – 2006	2007 – 2013	2014 – 2018
Log GDP pc in 2000	-.0042***	-.0088***	-.0005	.002
	(.0003)	(.0007)	(.001)	(.0022)
Agricultural employment	.0019	-.0103*	.0197***	.0184**
	(.0018)	(.0053)	(.0038)	(.0078)
Industrial employment	.0067***	-.0024	.0104***	.007*
	(.0008)	(.0026)	(.0029)	(.0041)
Education	.1489***	.2012***	.1453***	.0468
	(.011)	(.0368)	(.0289)	(.0617)
N	3008	1032	1136	840
Adj R^2	.998	.9993	.9991	.9984

* $p<0.05$, ** $p<0.01$, *** $p<0.001$
Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses. Country and year F.E. are included. Education is divided by 1000 for tractability.

5. The Effect of the Cohesion Policy

In this section, I study the effect of the EU Regional Policy. I use modeled real expenditures under various structural funds to proxy the financial support from the EU. I re-estimate my specifications, adding these proxies on the full sample and stable and top 5 sub-samples. Thus, I check if Cohesion Policy is able to promote regional GDP growth and convergence.

5.2 The Effect of Cohesion Policy in Full Sample

I estimate my specifications, adding the measures of EU support. I include sum of modeled real expenditures under Cohesion Fund (CF), European Development Fund (ERDF), and European Social Fund (ESF) and the interaction between the share of agricultural employment and modeled real expenditure under European Agricultural Fund for Rural Development (EAFRD). Table 10 shows the estimation results. These results are partially reconciled with the variation analysis as β coefficient in 2007 – 2013 is now positive. Moreover, the share of agricultural employment now shows a negative effect in 2000 – 2006 and 2014 – 2018. The share of industrial employment shows both positive and negative effects in different time periods. Interestingly, the coefficients on the sum of real expenditures are positive but insignificant. It raises concerns about the efficiency of EU Cohesion Policy.

Thus, the inclusion of the financial support from the EU solves, at least partially, two problems. Firstly, it partially reconciles regression results on the full sample with the results obtained via variation analysis. Secondly, it potentially solves the issue of endogeneity of the share of agricultural employment. However, the financial support itself can suffer from the reverse causality: Regions with low GDP per capita can be eligible to receive financial support that will increase their GDP per capita.

Table 10. Regressions with EU support in full sample. Source: Author's calculations

Programming period	2000 – 2006	2007 – 2013	2014 – 2018
Log GDP pc in 2000	-.0294***	.0007	-.0131***
	(.0024)	(.001)	(.0027)
EU Support	-.1041	.1063	.0981
	(.2032)	(.0676)	(.1421)
Agricultural employment	-.0101	.038*	-.1161***
	(.0343)	(.021)	(.037)
Agriculture × EAFRD	-.0055	-.0028	.0163***
	(.0055)	(.0027)	(.0051)
Industrial employment	-.0167***	.0143***	-.0068
	(.0054)	(.0043)	(.0059)
Education	.5809***	.2109***	.405***
	(.0762)	(.04)	(.086)
N	259	589	389
Adj R^2	.999	.9989	.9993

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses. Country and year F.E. are included. Education and EU Support are divided by 1000 for tractability.

5.3 The effect of Cohesion Policy in Stable Sub-sample

I check the robustness of the results from Table 10 by re-estimating all specifications on the stable sub-sample. Table 11 shows the estimation results. Overall, all specifications show convergence. Interestingly, EU support shows significant negative effect in 2014 – 2018. The share of agricultural employment shows varied effect (positive in 2007 – 2013, negative in 2014 – 2018). The interaction between agricultural employment and EAFRD has coefficients of different signs as well. The share of industrial employment shows varied signs but the coefficient on it remains always significant. Table 14 (in Annexes) shows estimation results for the top 5 sub-sample. The results are, however, approximately the same as in Table 11.

Table 11. Regressions with EU support in stable sub-sample. Source: Author's calculations

Programming period	2000 – 2018	2000 – 2006	2007 – 2013	2014 – 2018
Log GDP pc in 2000	-.0092***	-.0294***	-.0034	-.0077
	(.0007)	(.0024)	(.0023)	(.0047)
EU Support	.0272	-.1041	.0797	-.4172**
	(.0367)	(.2032)	(.11)	(.2052)
Agricultural employment	-.0025	-.0101	.0781**	-.3037***
	(.007)	(.0343)	(.0329)	(.0488)
Agriculture × EAFRD	-.0008	-.0055	-.0113**	.0493***
	(.0011)	(.0055)	(.0051)	(.0079)
Industrial employment	.0043***	-.0167***	.0424***	-.0207**
	(.0016)	(.0054)	(.009)	(.0096)
Education	.1763***	.5809***	.0321	.0139
	(.0176)	(.0762)	(.0605)	(.1057)
N	666	259	259	148
Adj R^2	.999	.9983	.9993	.9982

* p<0.05, ** p<0.01, *** p<0.001

Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses. Country and year F.E. are included. Education and EU Support are divided by 1000 for tractability.

I check the robustness of my results to the definition of EU support. Namely, I include modeled real expenditures separately into the model. Table 13 (in Annexes) shows that β coefficient is robust to the change of EU support proxy. However, only one support fund (ERDF) shows a significant coefficient. Thus, other support funds either have lower efficiency than ERDF or their significance is reduced by other factors, potentially including reverse causality.

I show that EU support has a varied effect on the GDP growth and convergence in the EU in 2000 – 2018 in this section. While some estimates of the coefficient on the EU support are positive and significant, the effect is not stable in terms of sign and stability. However, the convergence is robust to the inclusion of various EU support measures. The question about the existence of reverse causality remains open. Thus, further research is required to study the effectiveness of EU financial support.

My regression results partially disagree with Sala-i-Martin (1996) because I show that EU support can potentially increase growth rates. My results agree with Franks et al. (2018) by showing that the convergence slowed down and stopped after 2010. Similar to Dall'erba and le Gallo (2008) and Boldrin and Canova (2001), I support the limited effectiveness of EU support funds as their positive effect is not stable. I partly confirm the results of Becker, Egger, and von Ehrlich (2010) by finding limited positive association between EU support and GDP per capita growth rates.

5. Possibilities for Further Research

I study GDP per capita growth and convergence in the EU in 2000 – 2018. I use a variation of regional GDP per capita as the measure of dispersion and estimate regressions using growth rates as the main dependent variable. During my analysis, I encountered issues that provide possibilities for further research. Firstly, Figure 9 provides evidence for the existence of multiple groups of regions that potentially are related to "convergence clubs." Further research is needed to understand better the nature of these groups and the reasons for their existence. Secondly, I use modeled real expenditures under different EU support funds. However, the usage of actual expenditures is preferred and could potentially reveal more information about the effect of the EU Regional Policy. These data are not readily available and, thus, would require additional data collection. Thirdly, the puzzle of the positive influence of the share of agricultural employment remains unsolved. Further study is required to find out if it is a feature of data or an indicator of statistical problems such as endogeneity. Fourthly, EU support does not a show stable effect in my results. It can be potentially due to the reverse causality. Hence, the research using Research Discontinuity Design or Instrumental Variables would allow me to study the causal and "cleaner" effect of EU support on GDP growth and convergence. Lastly, more complicated models could, in theory, give more profound results. For instance, Vector Autoregression (VAR) would allow me to study the convergence of multiple variables simultaneously.

6. Conclusion

In conclusion, I study the regional GDP per capita growth and convergence in the EU member states in 2000 – 2018. I use two measures that can show divergence or convergence of regions. Firstly, I use variation as the measure of dispersion. Variation analysis shows that the EU regions initially converged in early 2000s. However, they began to diverge in 2004 based on the variation of log GDP per capita. Importantly, the variation indicates divergence only if I do not include controls for countries. I find divergence for regions in both old and new EU member countries. Secondly, I use the model of β-convergence for regression analysis. On full sample, regression results do not confirm the results obtained via the variation analysis. However, stable and top 5 sub-samples show results that agree with variation analysis. I show that there are multiple groups of regions that differ in initial GDP per capita level and growth rates. The group of low initial GDP per capita and high growth rates mixes with the group of high GDP per capita and low growth rates and potentially causes the discrepancy between regression analysis and variation analysis.

I augment my regressions with additional control variables, including the share of agriculture in employment, support from the EU under various funds, and other factors. My results suggest that the convergence is robust to the inclusion of additional characteristics. However, there are potential concerns related to econometrical problems of endogeneity and multicollinearity that require further study. Overall, my results agree with existing research. I support the view of the limited efficiency of EU support programs (Sala-i-Martin 1996; Boldrin and Canova 2001). I expand the results of Franks et al. (2018) by looking at the newer time periods and find that overall

GDP per capita variation falls after 2015 and showing that within-country variation decreases in the long run.

Overall, regional convergence is an important topic for the EU, as convergence fosters equality of the regions and countries. Among other measures, the EU uses financial support via structural funds to promote the equality of regions. However, there is mixed evidence regarding the efficiency of the EU Cohesion Policy. Thus, it is important to study the issue further to understand whether current policy measures are fully effective. Moreover, it is crucial to determine whether the EU policies may actually damage or delay the convergence of EU regions.

Summary

In this thesis, I study GDP per capita growth in EU regions. Specifically, this paper contributes to the research on convergence and divergence of EU regions. I perform my analysis in two steps. Firstly, I use the variation of log GDP per capita in regions as the measure of dispersion following Cappelen et al. (2003). I show that regions diverge in about 2004 – 2015 with a tendency to converge after 2015. However, within-country variance is relatively stable in 2000 – 2018 and decreases after 2015. Thus, the divergence of countries, between-country variation, causes overall divergence of EU regions. Secondly, I use β-converegence model following Fagerberg and Verspagen (1996) to study GDP per capita convergence in a regression framework. A simple model with only one variable, log initial GDP per capita, shows varied results that do not agree with variation analysis. This discrepancy is explained by new regions and the existence of groups of regions that have different initial GDP per capita levels and show different growth rates. Some of these groups converge in 2018 and potentially cause regressions to estimate overall convergence.

I include regional characteristics and modeled real expenditures under various EU structural funds. The coefficient on initial log GDP per capita is robust to these additions. However, I find potential problems (such as the potential presence of reverse causality and endogeneity) with the share of agricultural employment and real expenditures under EU structural funds. However, the solution to these problems remains without the scope of this thesis and constitutes a possibility for further research.

References

Anonymous. 2013. “Romania: On the Way to Recovery through Prudent Macroeconomic Management.” The World Bank. 2013. https://www.worldbank.org/en/results/2013/04/11/romania-on-the-way-to-recovery-through-prudent-macroeconomic-management.

Becker, Sascha O., Peter H. Egger, and Maximilian von Ehrlich. 2010. “Going NUTS: The Effect of EU Structural Funds on Regional Performance.” *Journal of Public Economics* 94 (9–10): 578–90. https://doi.org/10.1016/j.jpubeco.2010.06.006.

Boldrin, M., and F. Canova. 2001. “Inequality and Convergence in Europe’s Regions: Reconsidering European Regional Policies.” *Economic Policy* 16 (32): 206–53. https://doi.org/10.1111/1468-0327.00074.

Calegari, Elena, Enrico Fabrizi, Gianni Guastella, and Francesco Timpano. 2021. “EU Regional Convergence in the Agricultural Sector: Are There Synergies between Agricultural and Regional Policies?” *Papers in Regional Science* 100 (1): 23–50. https://doi.org/10.1111/pirs.12569.

Cappelen, Aadne, Fulvio Castellacci, Jan Fagerberg, and Bart Verspagen. 2003. “The Impact of EU Regional Support on Growth and Convergence in the European Union.” *JCMS: Journal of Common Market Studies* 41 (4): 621–44. https://doi.org/10.1111/1468-5965.00438.

Dabrowski, Marek. 2010. “The Global Financial Crisis: Lessons for European Integration.” *Economic Systems* 34 (1): 38–54. https://doi.org/10.1016/j.ecosys.2010.01.002.

Dall’erba, Sandy, and Julie le Gallo. 2008. “Regional Convergence and the Impact of European Structural Funds over 1989-1999: A Spatial Econometric Analysis*.” *Papers in Regional Science* 87 (2): 219–44. https://doi.org/10.1111/j.1435-5957.2008.00184.x.

European Commission. 2021. “European Structural and Investment Funds 2021 Summary Report of the Programme Annual Implementation Reports Coveringimplementation in 2014-2020.” Articles/implementation_2021_report_en.pdf.

———. 2022a. “The EU’s Main Investment Policy.” 2022.

———. 2022b. “Cohesion Fund.” July 1, 2022.

Eurostat. 2021. “Eurostat Regional Yearbook.” Articles/regions2021.pdf.

Fagerberg, Jan, and Bart Verspagen. 1996. “Heading for Divergence? Regional Growth in Europe Reconsidered*.” *JCMS: Journal of Common Market Studies* 34 (3): 431–48. https://doi.org/10.1111/j.1468-5965.1996.tb00580.x.

———. 2002. “Technology-Gaps, Innovation-Diffusion and Transformation: An Evolutionary Interpretation.” *Research Policy* 31 (8–9): 1291–1304. https://doi.org/10.1016/S0048-7333(02)00064-1.

Fagerberg, Jan, Bart Verspagen, and Marjolein Caniëls. 1997. “Technology, Growth and Unemployment across European Regions.” *Regional Studies* 31 (5): 457–66. https://doi.org/10.1080/00343409750132252.

Franks, Jeffrey, Bergljot Barkbu, Rodolphe Blavy, William Oman, and Hanni Schoelermann. 2018. “Economic Convergence in the Euro Area: Coming Together or Drifting Apart?” 2018/010. Working Paper.

Ramajo, Julián, Miguel A. Márquez, Geoffrey J.D. Hewings, and María M. Salinas. 2008. “Spatial Heterogeneity and Interregional Spillovers in the European Union: Do Cohesion

Policies Encourage Convergence across Regions?” *European Economic Review* 52 (3): 551–67. https://doi.org/10.1016/j.euroecorev.2007.05.006.

Rodríguez-Pose, Andrés. 2013. “Do Institutions Matter for Regional Development?” *Regional Studies* 47 (7): 1034–47. https://doi.org/10.1080/00343404.2012.748978.

Sala-i-Martin, Xavier. 1996. “Regional Cohesion: Evidence and Theories of Regional Growth and Convergence.” *European Economic Review* 40 (6): 1325–52. https://EconPapers.repec.org/RePEc:eee:eecrev:v:40:y:1996:i:6:p:1325-1352.

Sterlacchini, Alessandro. 2008. “R&D, Higher Education and Regional Growth: Uneven Linkages among European Regions.” *Research Policy* 37 (6–7): 1096–1107. https://doi.org/10.1016/j.respol.2008.04.009.

Annexes

Table 12. Regressions with additional control variables in top 5 sub-sample. Source: Author’s calculations

Programming period	2000 – 2006	2007 – 2013	2014 – 2018
Log GDP pc in 2000	-.0092***	-.0007	-.0024*
	(.0007)	(.0012)	(.0013)
Agricultural employment	-.0103*	.0157***	.0141**
	(.0059)	(.0042)	(.007)
Industrial employment	-.0008	.0074*	.0068*
	(.003)	(.004)	(.0038)
Education	.2774***	.1317***	.1767***
	(.0415)	(.0324)	(.0457)
N	1032	1136	840
Adj R^2	.9993	.9989	.9996

* p<0.05, ** p<0.01, *** p<0.001

Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses. Country and year F.E. are included. Education is divided by 1000 for tractability.

Table 13. Effects of EU support for different measures in stable sub-sample. Source: Author's calculations

Support measure	**CF**	**ERDF**	**ESF**	**CF+ERDF+ESF**
Log GDP pc initial	-.0093***	-.0038***	-.0044***	-.0092***
	(.0006)	(.0003)	(.0003)	(.0007)
EU Support	.0484	.2085***	.0525	.0272
	(.0656)	(.048)	(.0686)	(.0367)
Agriculture × EAFRD	-.0039	.0156***	.0083	-.0025
	(.0065)	(.0054)	(.0055)	(.007)
N	666	2565	2576	666
Adj. R2	.9982	.9985	.9985	.9982

* p<0.05, ** p<0.01, *** p<0.001
Note: Dependent variable – compound growth rate of GDP per capita. Robust (white) standard errors are in parentheses. Country and year F.E. are included. EU support measures are divided by 1000 for tractability.

Table 14. Regressions with EU support in top 5 sub-sample. Source: Author's calculations

Programming period	2000 – 2018	2000 – 2006	2007 – 2013	2014 – 2018
Log GDP pc in 2000	-.0072***	-.0277***	-.0028	-.0067*
	(.0007)	(.0027)	(.0029)	(.004)
EU Support	.1194***	.0656	.0974	-.0587
	(.0401)	(.2171)	(.1209)	(.2171)
Agricultural employment	-.0195**	-.0254	.08*	-.3597***
	(.008)	(.0372)	(.0417)	(.054)
Agriculture × EAFRD	.0023*	-.0022	-.0117*	.0572***
	(.0012)	(.0062)	(.0064)	(.0083)
Industrial employment	.009***	-.0054	.0403***	.0044
	(.0021)	(.0062)	(.0124)	(.0155)
Education	.1947***	.6005***	.0479	.0343
	(.0171)	(.0759)	(.0685)	(.1216)
N	533	210	210	113
Adj R^2	.999	.998	.9993	.9981

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note: Dependent variable – compound growth rate of GDP per capita in respective years. Robust (white) standard errors are in parentheses. Country and year F.E. are included. Education and EU Support are divided by 1000 for tractability.

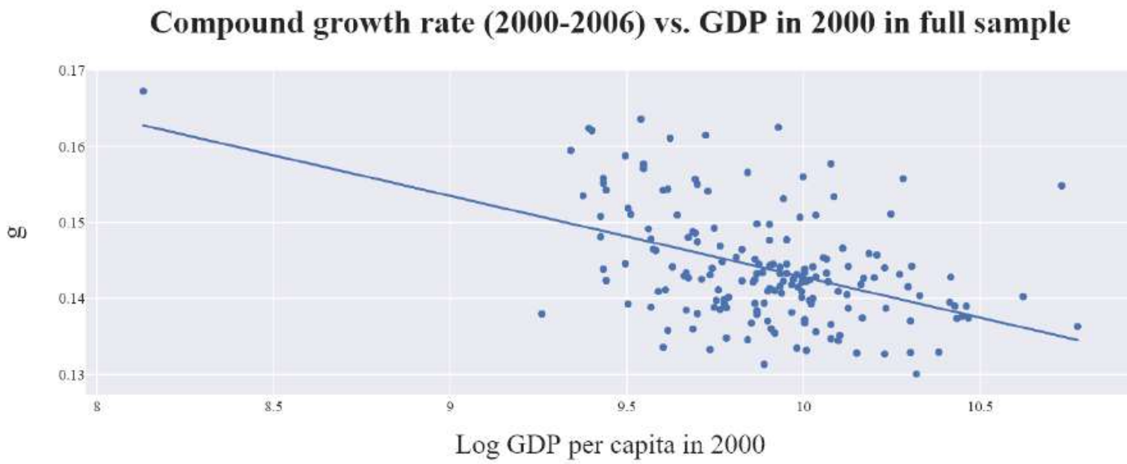

Figure 10. Scatter plot of g vs. initial conditions in full sample for period 1. Source: Author's calculations

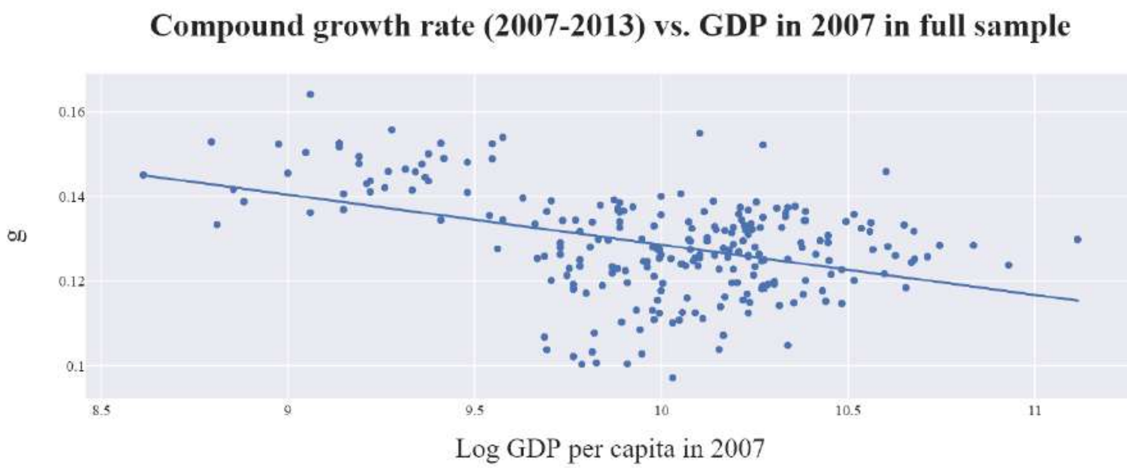

Figure 11. Scatter plot of g vs. initial conditions in full sample for period 2. Source: Author's calculations

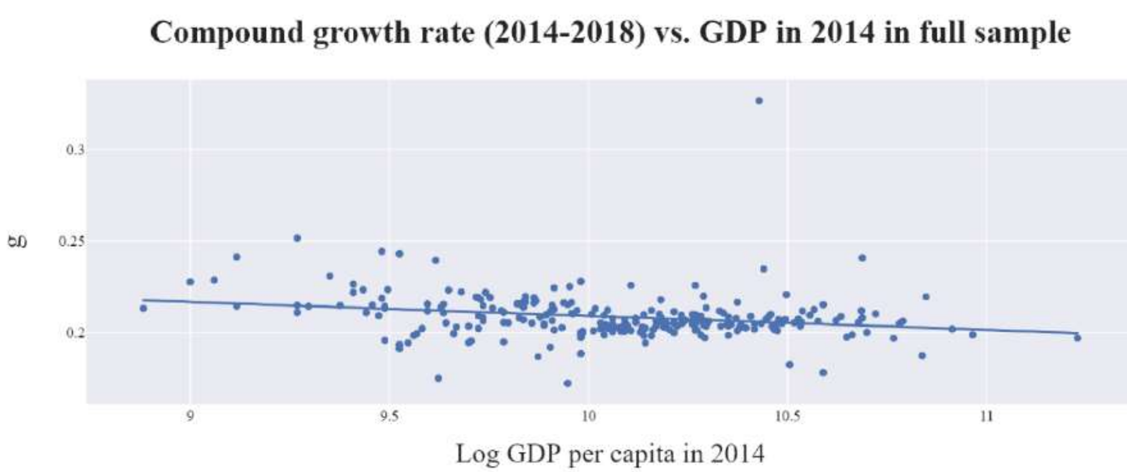

Figure 12. Scatter plot of g vs. initial conditions in full sample for period 3. Source: Author's calculations

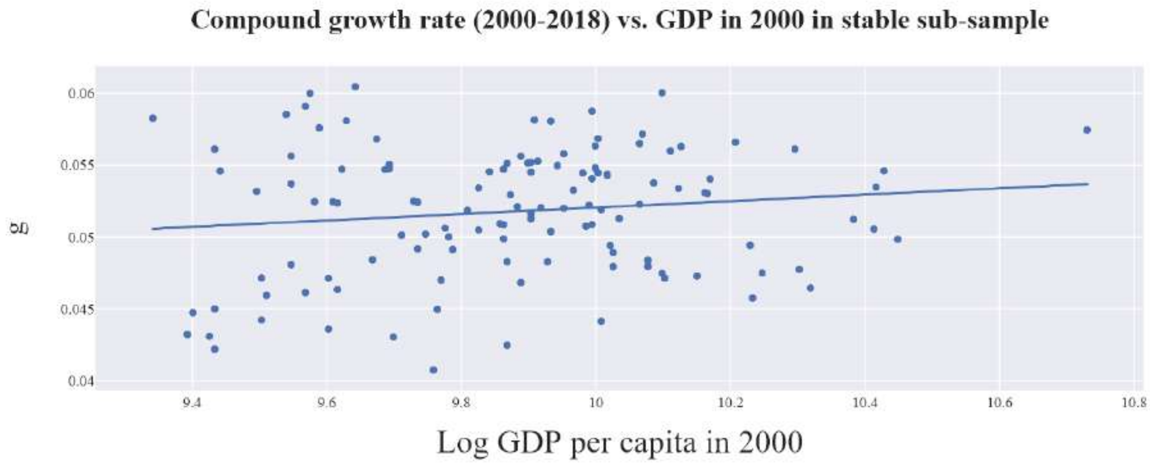

Figure 14. Scatter plot of g vs. initial conditions in stable sub-sample, pooled. Source: Author's calculations

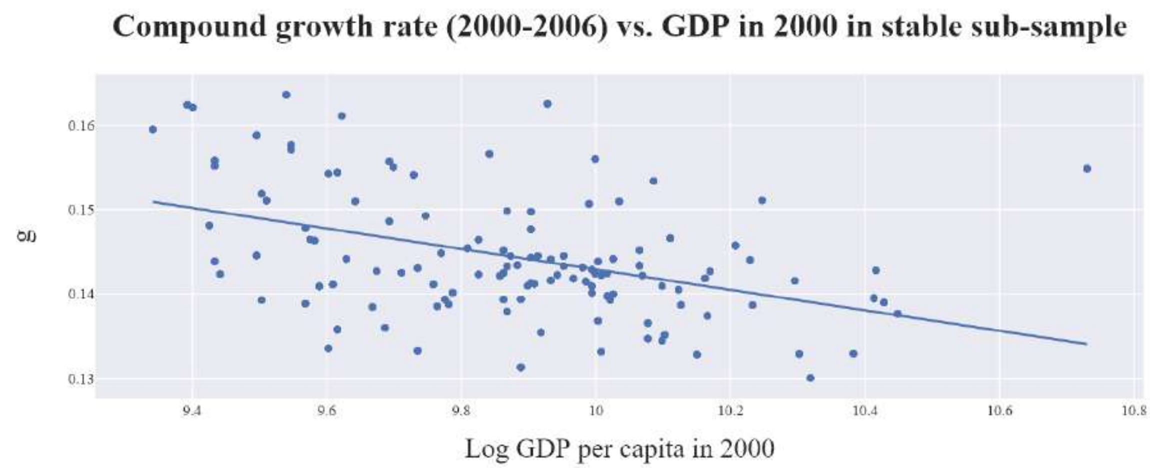

Figure 15. Scatter plot of g vs. initial conditions in stable sub-sample for period 1. Source: Author's calculations

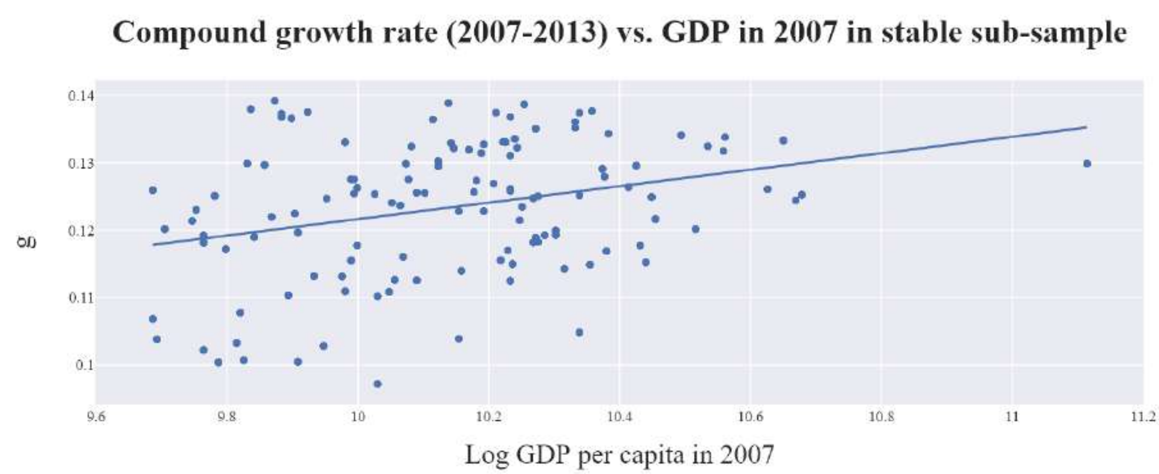

Figure 16. Scatter plot of g vs. initial conditions in stable sub-sample for period 2. Source: Author's calculations

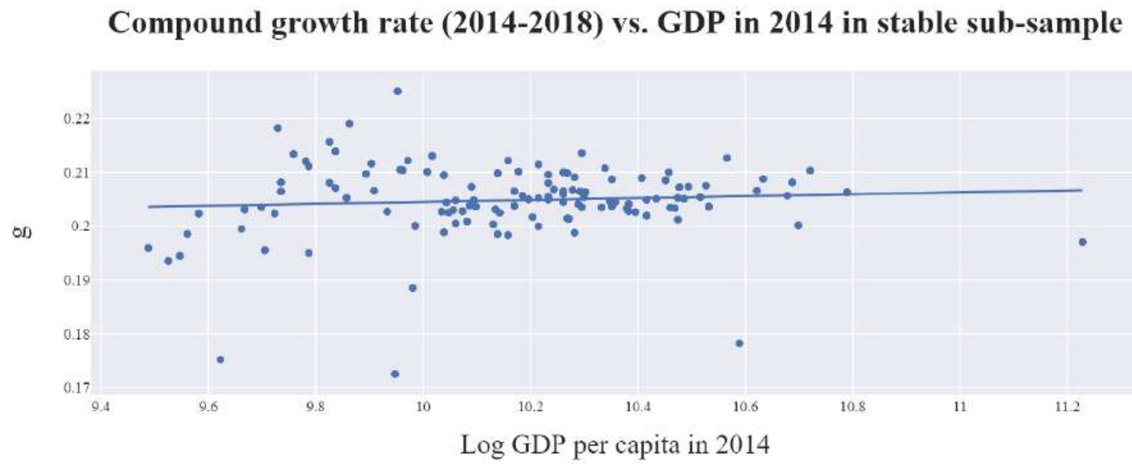

Figure 17. Scatter plot of g vs. initial conditions in stable sub-sample for period 3. Source: Author's calculations

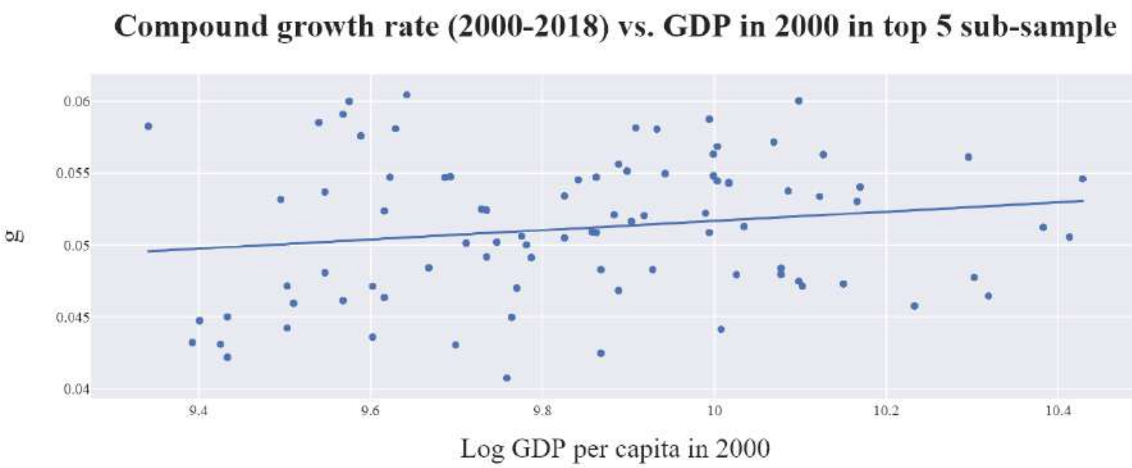

Figure 18. Scatter plot of g vs. initial conditions in top 5 sub-sample, pooled. Source: Author's calculations

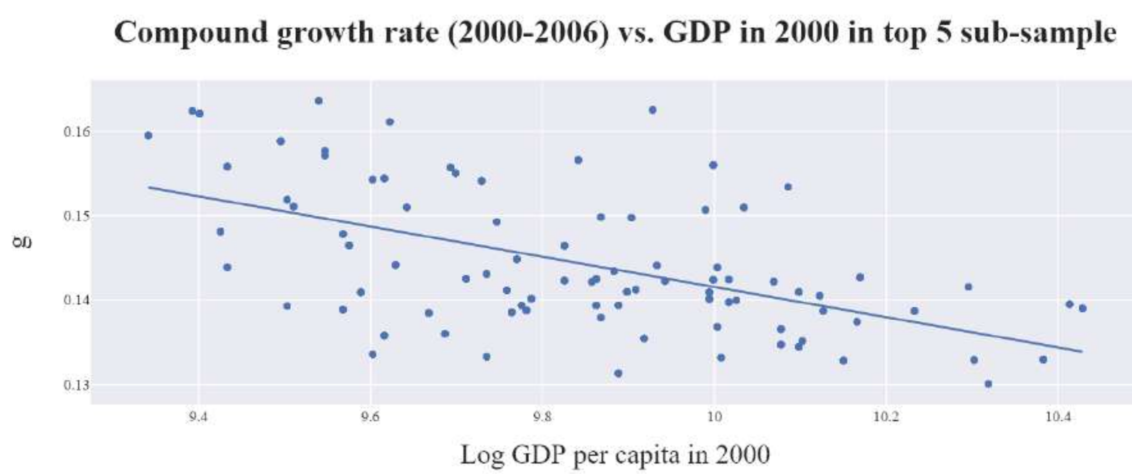

Figure 19. Scatter plot of g vs. initial conditions in top 5 sub-sample for period 1. Source: Author's calculations

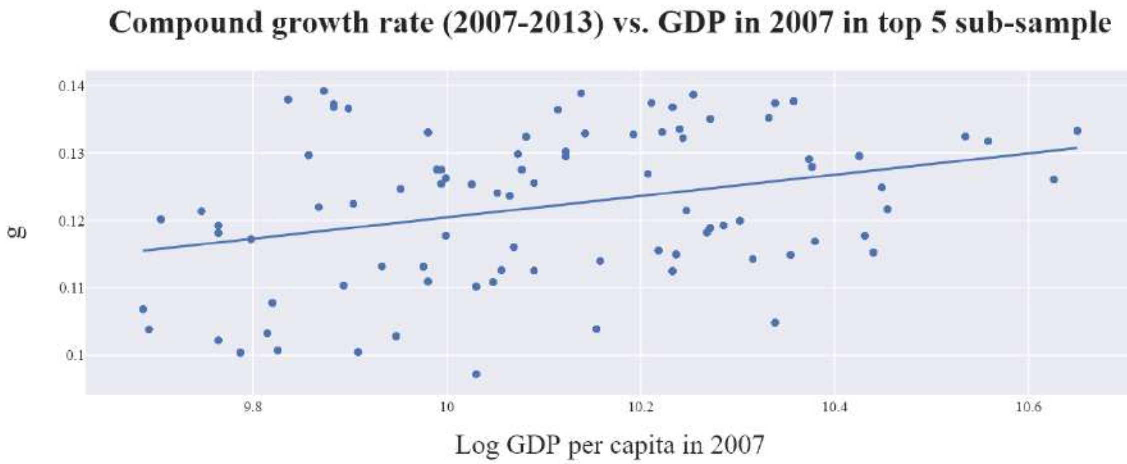

Figure 20. Scatter plot of g vs. initial conditions in top 5 sub-sample for period 2. Source: Author's calculations

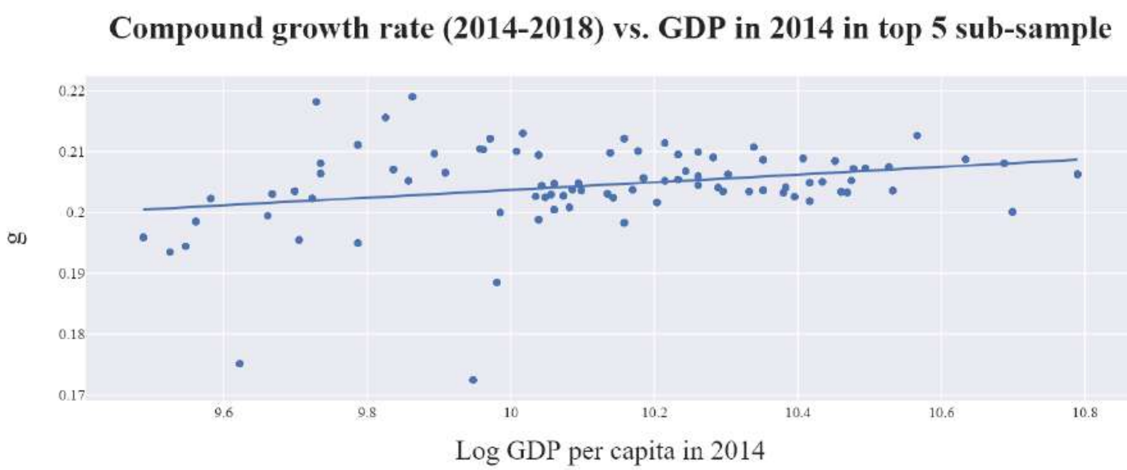

Figure 21. Scatter plot of g vs. initial conditions in top 5 sub-sample for period 3. Source: Author's calculations

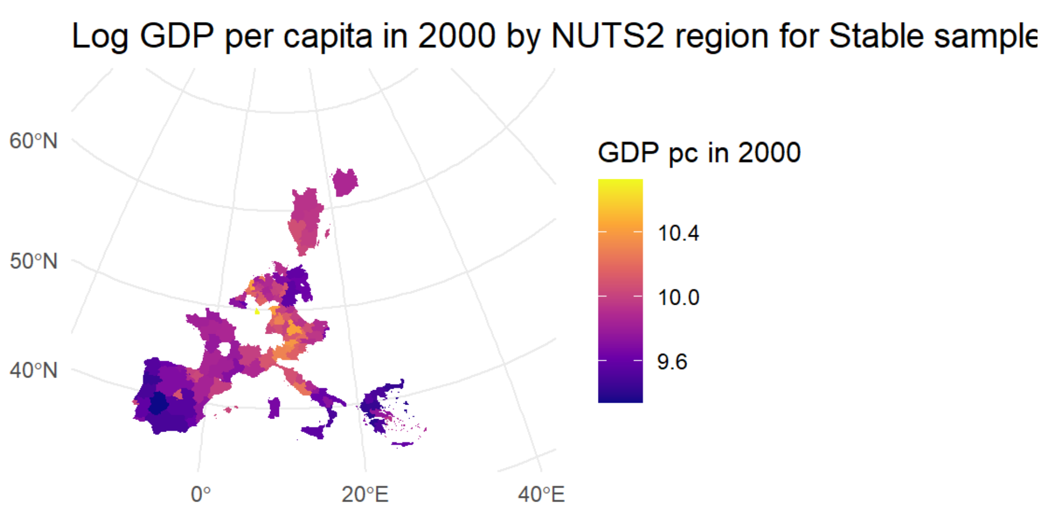

Figure 22. Map of regions included in the stable sub-sample. Color - Log GDP per capita in 2000. Source: Author's calculations

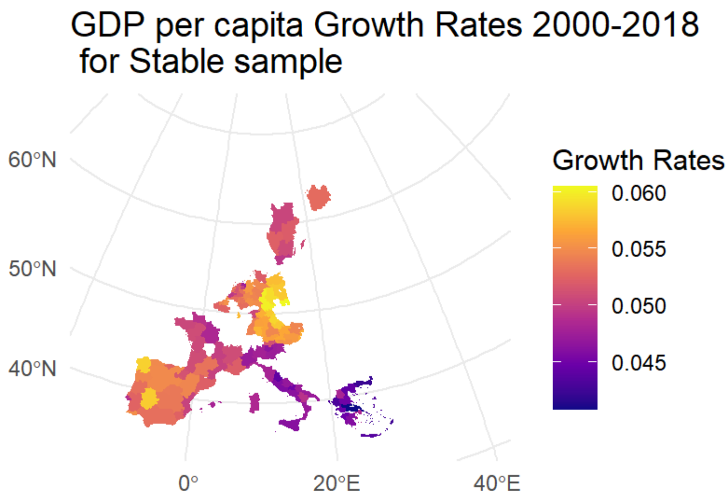

Figure 23. Map of regions in the stable sub-sample. Color - compound growth rates from 2000 to 2018. Source: Author's calculations

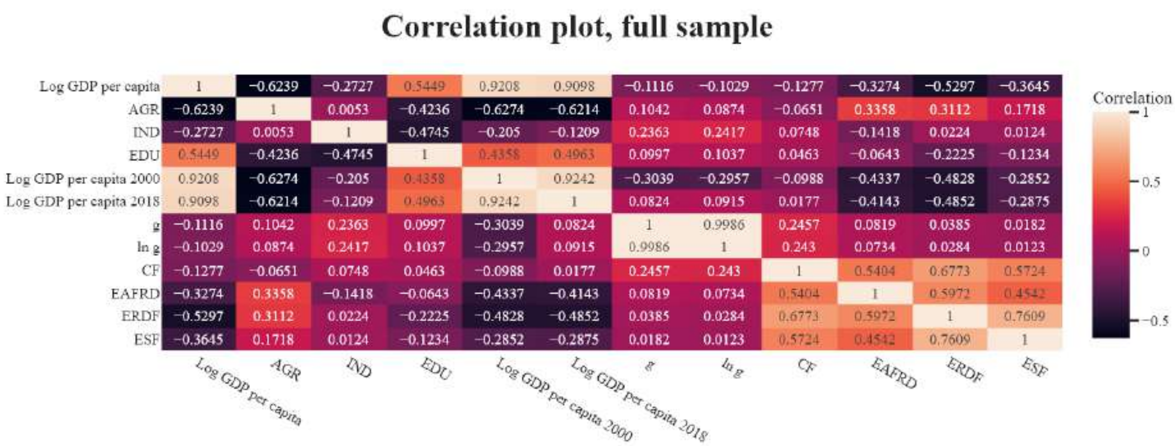

Figure 24. Correlation plot for all variables in full sample. Source: Author's calculations

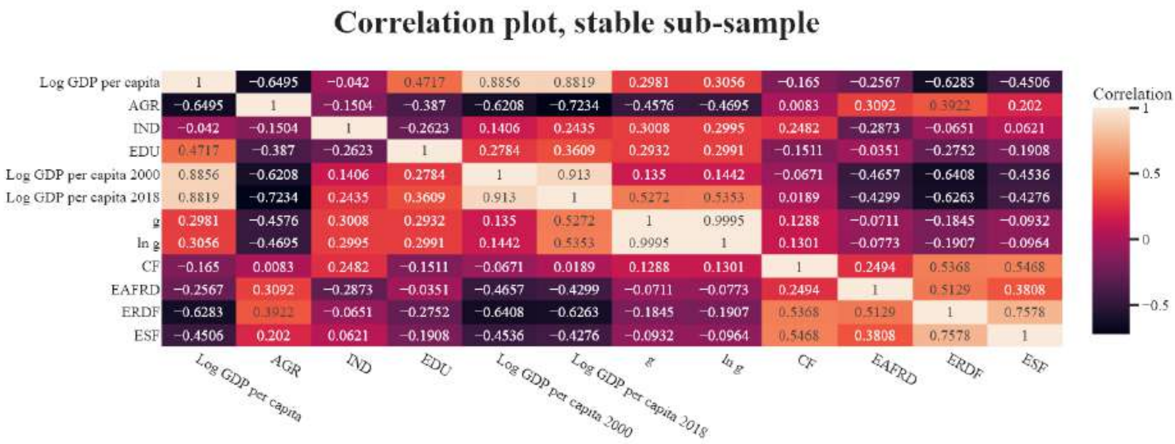

Figure 25. Correlation plot for all variables in stable sub-sample. Source: Author's calculations

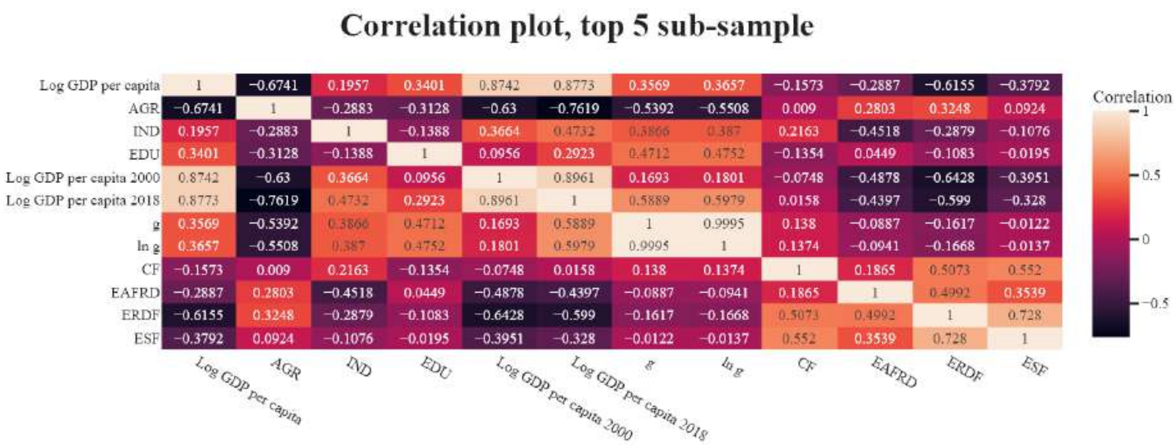

Figure 26. Correlation plot for all variables in top 5 sub-sample. Source: Author's calculations

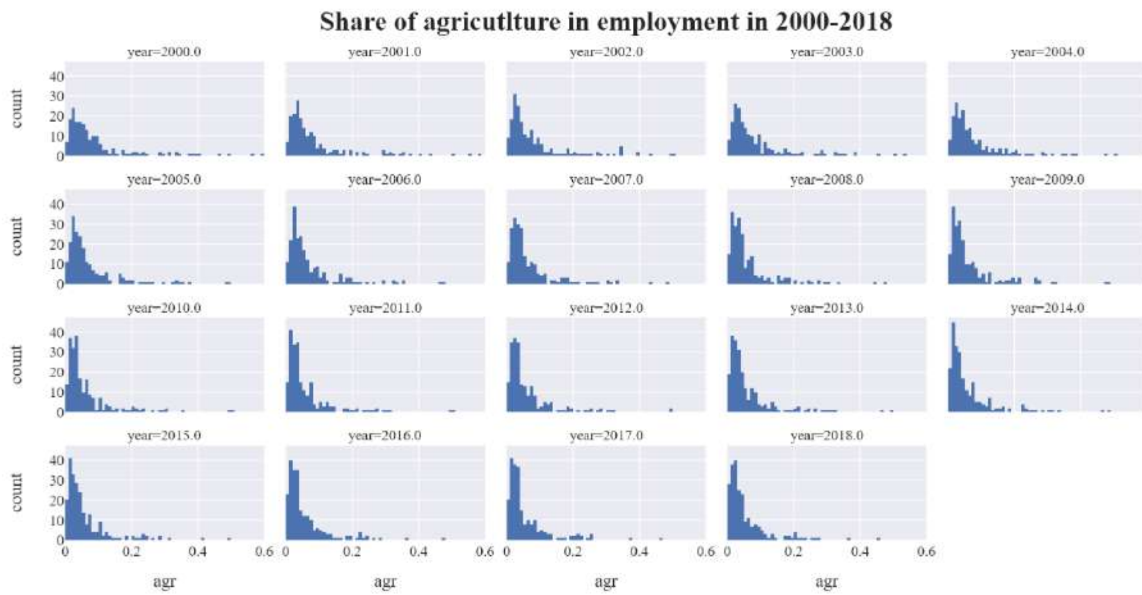

Figure 27. The share of agriculture in employment in full sample by year. Source: Author's calculations

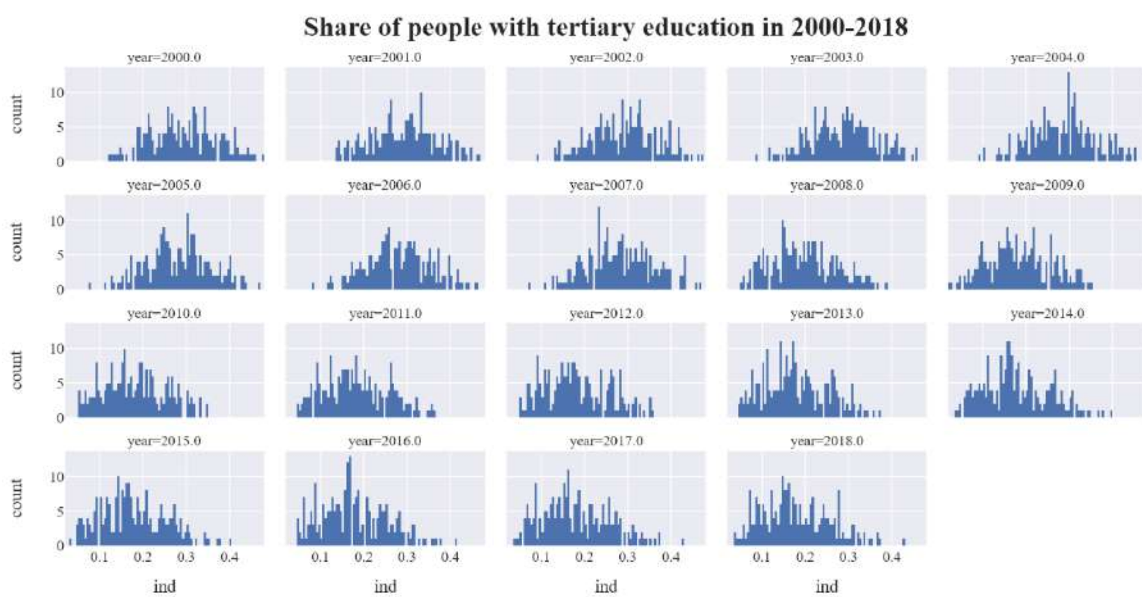

Figure 28. The share of people with tertiary education in full sample by year. Source: Author's calculations

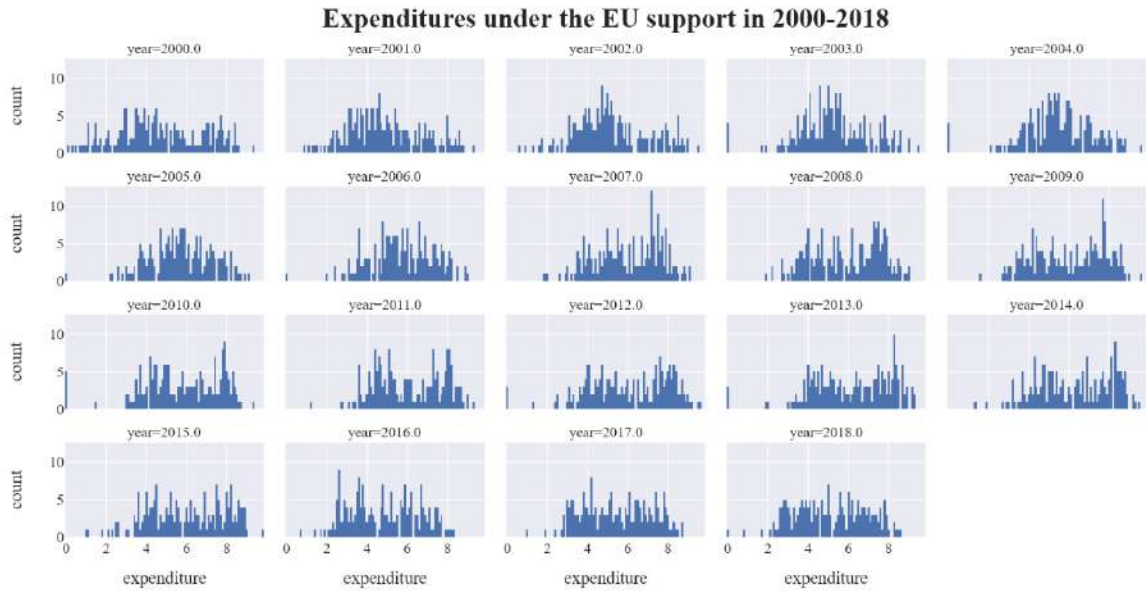

Figure 29. Expenditures under financial support from the EU in full sample by year. Source: Author's calculations

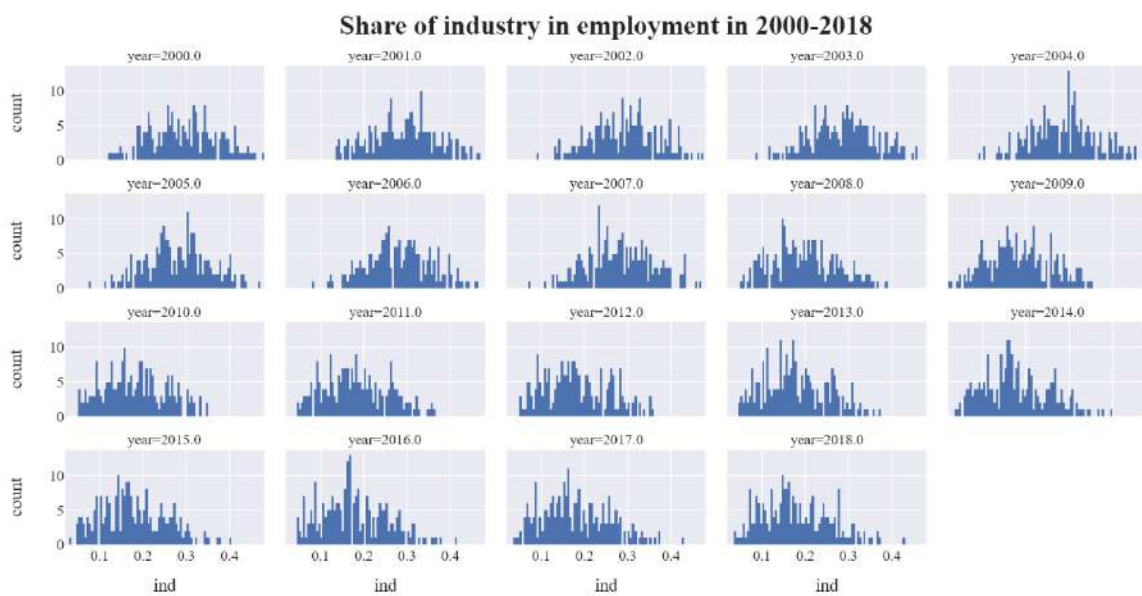

Figure 30. Share of industry in employment in full sample by year. Source: Author's calculations

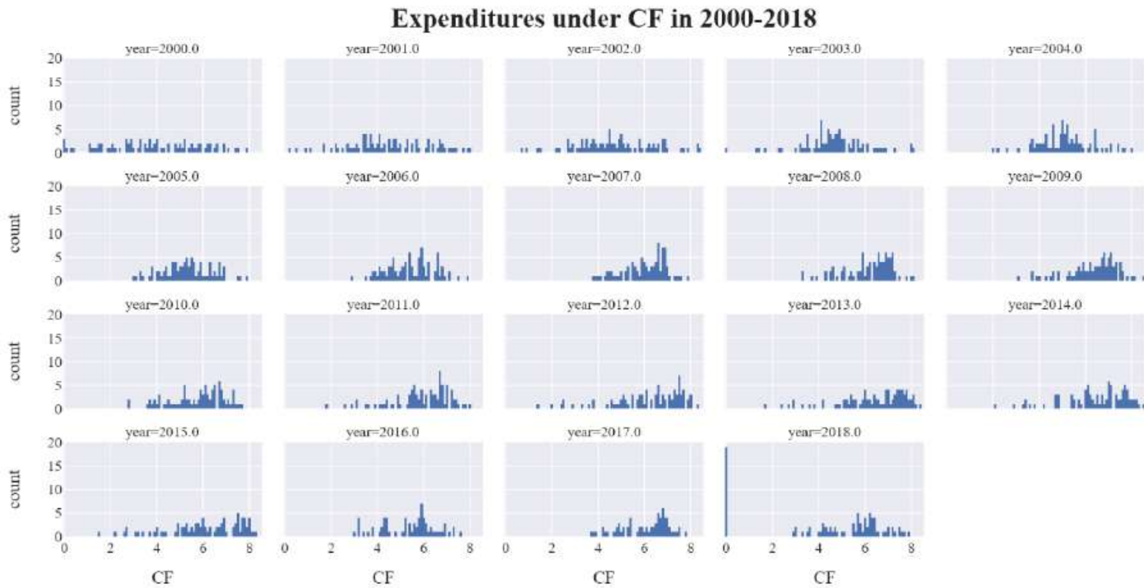

Figure 31. Modeled real expenditures under Cohesion Fund (CF) in full sample by year. Source: Author's calculations

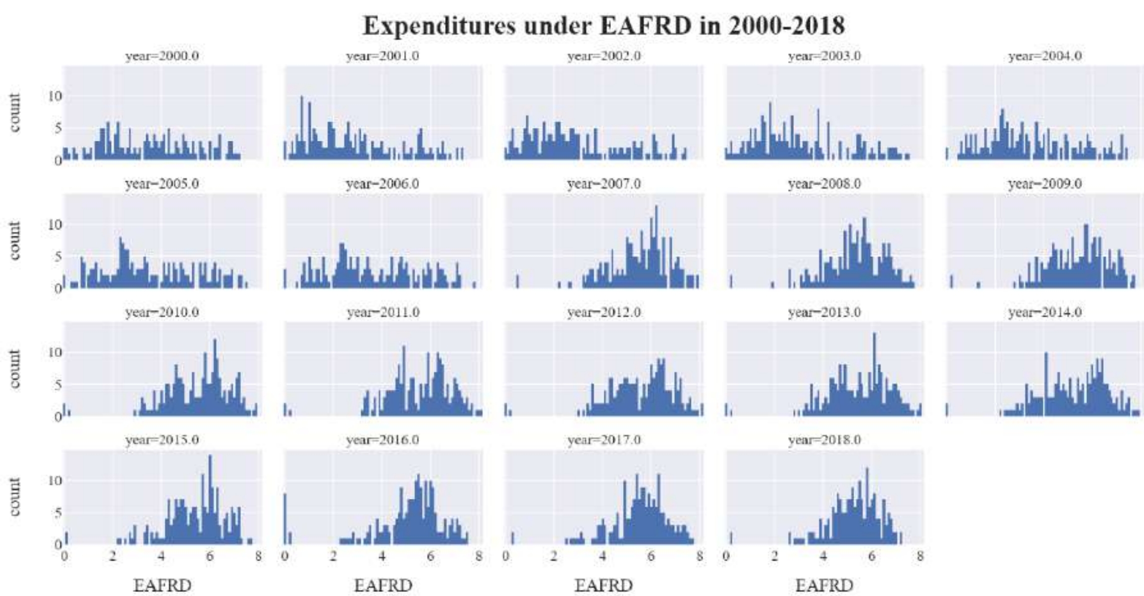

Figure 32. Modeled real expenditures under European Agricultural Fund for Rural Development (EAFRD) in full sample by year. Source: Author's calculations

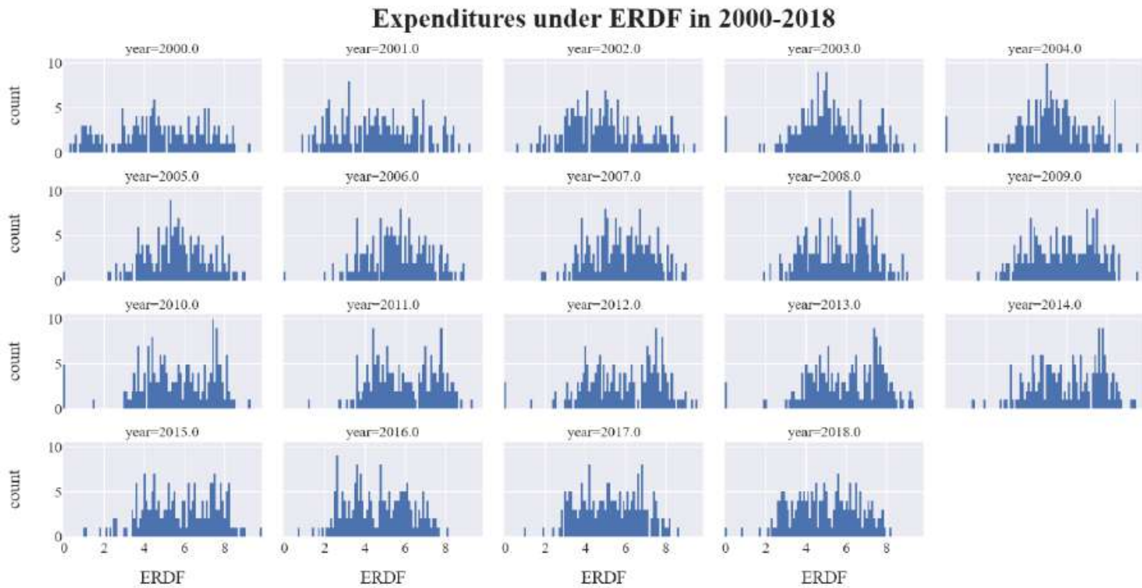

Figure 33. Modeled real expenditures under European Regional Development Fund (ERDF) in full sample by year. Source: Author's calculations

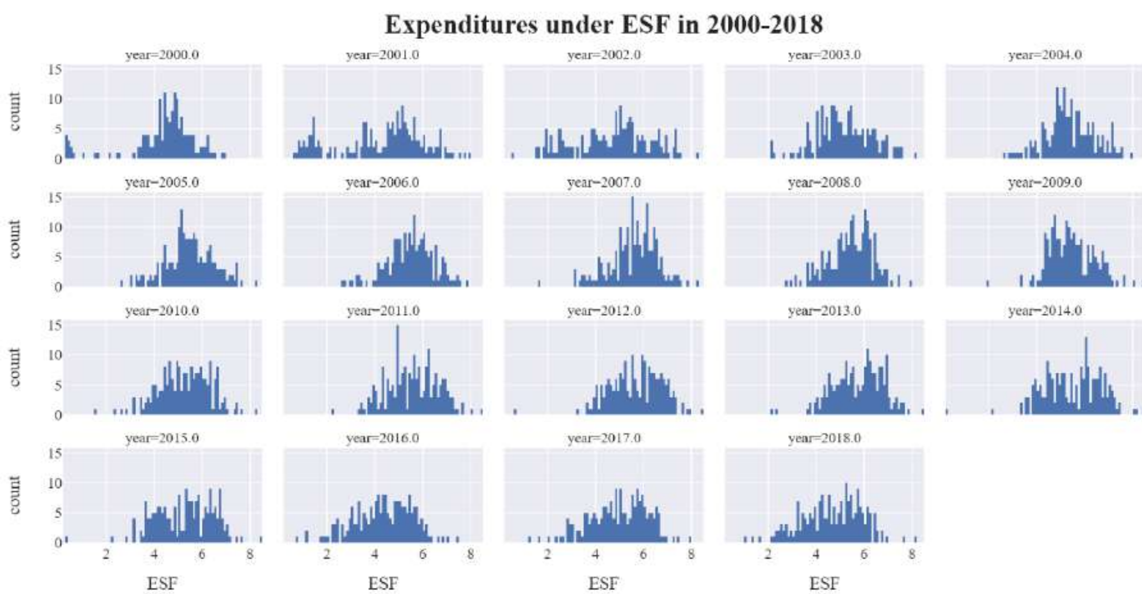

Figure 34. Modeled real expenditures under European Support Fund (ESF) in full sample by year. Source: Author's calculations