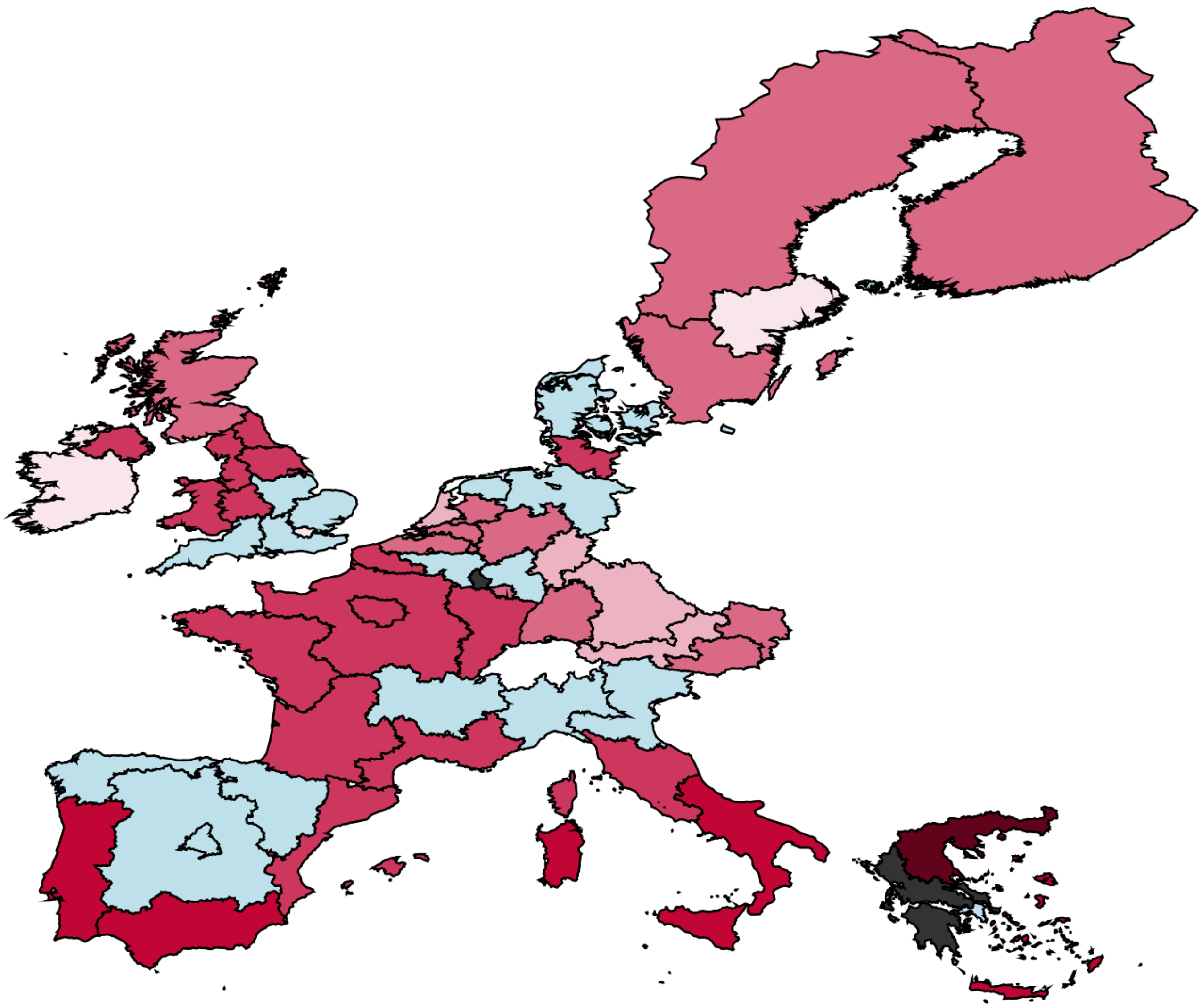
Konrad von Lyncker



Macroeconomic Imbalances in the Process of European Integration: Theoretical Considerations and Empirical Evidence

Macroeconomic Imbalances in the Process of European Integration: Theoretical Considerations and Empirical Evidence

Universität Hamburg

Fakultät für Wirtschafts- und Sozialwissenschaften

Dissertation

Zur Erlangung der Würde eines Doktors der

Wirtschafts- und Sozialwissenschaften

"Dr. rer. pol."

(gemäß der PromO vom 24. August 2010)

vorgelegt von

Konrad Nikolaus Freiherr von Lyncker-Ehrenkrook

aus Bellville

Hamburg, den 31. März 2016

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Datum der Disputation: 13. Juli 2016

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2016

to my family

Acknowledgements

The last four years have been a very intense time. I am deeply grateful to have been able to share the ups and downs with some very special people.

I would particularly like to thank my colleague and friend Rasmus Thönnessen. In a period when I feared losing grip on my dissertation, we started a joint work about regional convergence (Chapter 6). Working with Rasmus gave me the research experience I needed to accomplish my further studies.

A very special thanks goes to my supervisor Thomas Straubhaar, who, while invariably granting me full academic freedom was always happy to give valuable feedback. I deeply appreciate your unequivocal support in academic, professional and personal matters. Thank you also for your unconditionally liberal spirit, which makes every discussion with you a delightful experience.

I further wish to thank my second supervisor, Michael Bräuninger, who provided me with unreserved academic support and never failed to lend me an ear in times of need. Thanks also to Edgar Baake, Ulrich Blum, and Georg Koopmann for valuable feedback on my research. Moreover, I would like to express my gratitude to the whole team at the Chair for International Economics for a pleasant and inspiring work environment. In advance, I want to thank the members of the board of examiners for their effort in reviewing my dissertation.

I am very grateful for the love of my family, who have accompanied and supported me throughout the ups and downs of the last four years. Lastly, I want to thank my girlfriend Thekla, who has been my greatest support and solid rock in the last two years. Thank you for unconditionally loving and believing in me.

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Chapter 1

Introduction

> A debtor nation does not love its creditor, and it is fruitless to expect feelings of goodwill from France, Italy, and Russia towards this country [Great Britain] or towards America, if their future development is stifled for many years to come by the annual tribute which they must pay us.
>
> — John Maynard Keynes (1919, p. 261),
> The Economic Consequences of the Peace

1.1 Motivation

The brilliance of John Maynard Keynes roots in his academic perspective, which was that of a political economist rather than that of an economist in the modern sense. Keynes acknowledged the close connection between politics and economics and their far-reaching implications for the well-being of and peace between societies. The book that was to found his reputation as a far-sighted, reflecting and highly honourable economist was entitled 'The Economic Consequences of the Peace'. It contained a review of his experiences as the official representative of the British Treasury during the Paris Peace Conference in 1919. After a terrifying war, Keynes (1919) recognized the importance to fill up ditches instead of preserving them or digging new ones. The above quote refers to war loans accommodated between the allied nations, for which Keynes advocated full mutual debt reliefs.

It took another terrifying war before Europe realized that ditches had to be filled up to maintain peace between European nations. The process of European integration after World War II illustrates how a supranational economic agenda is capable of providing not only economic well-being but also political and social harmony. Against this background, it seems tragic that the prolonged story of success of European integration has apparently came to a halt; nearly a century after Keynes published his 'Economic Consequences', Europe (more precisely: the eurozone) faces a severe division in economic and also political terms. External imbalances between nations in the geographic core and in the European periphery have emerged and accumulated, thereby inevitably causing diverging net foreign asset positions and splitting Europe into borrower and creditor states. Rather than mitigating this borrower-creditor-division, the introduction of bail-out measures within the eurozone in 2010 contributed to institutionalizing it by relocating large parts of imbalances from the private sector to a public level.

As the initial quote suggests, Keynes regarded a division between borrower and creditor countries as a threat to political and ultimately social harmony. With view to the allied borrower nations he was afraid that "[t]hey may be expected, therefore, to make constant attempts to evade or escape payment, and these attempts will be a constant source of international friction and ill-will for many years to come." (Keynes, 1919, p. 261). It is remarkable how accurately Keynes' prophecy renders the current political situation in Europe, where the political tone between eurozone member states has indeed sharply heated up throughout the Euro crisis.

This spells out the pivotal importance of macroeconomic imbalances, not only from an economic, but also from a political point of view. If the EU and in particular the eurozone fail to abolish macroeconomic imbalances between member states, the project of European integration is at risk of failing to achieve its very initial objective, i.e. "to ensure the economic and social progress of their countries by common action in eliminating the barriers which divide Europe" (European Economic Community, 1957, p. 1).

Against this background, this dissertation attempts to shed light on macroeconomic imbalances and growth divergence across Europe and the eurozone. The agenda is twofold: the first focus is on causes of macroeconomic imbalances from a theoretical perspective. In this strict sense, macroeconomic imbalances comprise external imbalances, which are defined as substantial deficits or surpluses in the current and capital account. Throughout this dissertation, the broader sense of macroeconomic imbalances also embraces the corresponding shifts in consumption, investment, (wage) inflation, external competitiveness and wealth. The second focus is on income growth patterns across European regions from an empirical perspective. More specifically, the target is to detect growth convergence clubs and to investigate their evolution and their drivers.

The implementation of this agenda is based on five separate studies. No overall consolidation of these studies was undertaken in order to ensure that each study keeps its independence. Theoretical implications of converging nominal interest rates on macroeconomic variables are addressed in Chapter 2 and Chapter 3. Chapter 4 presents a Monte Carlo study, which evaluates different clustering procedures to detect convergence clubs in panel data. Chapter 5 and Chapter 6 attempt to identify regional convergence clubs in Europe, using panel data on two different levels of aggregation (NUTS-1 and NUTS-2).

More detailed summaries of all studies, findings, and conclusions are provided in Sections 1.3–1.4.

The remainder of this introductory chapter is organized as follows:. Section 1.2 gives an overview of the most relevant literature referred to in this dissertation. Section 1.3 sketches out strategies, agendas and results of the five single studies presented in Chapters 2–6. A résumé of all findings and challenges of the studies is drawn in Section 1.4. Reflections on the results are presented in Section 1.5.

1.2 State of the Art

A major part of research on macroeconomic imbalances within the eurozone was done at times of a prospering and well-functioning currency union. In a seminal paper, Blanchard and Giavazzi (2002) argue that the appearance of current account deficits in the eurozone's peripheral countries indicates economic catch-up and is therefore a sign of a well-functioning currency union. In this view, cross-country inflation differentials can be explained by the Balassa-Samuelson-effect (Balassa, 1964; Samuelson, 1964), which postulates that price increases tend to be larger in low income countries catching up in terms of growth and productivity. In 2011, Giavazzi and Spaventa (2011) challenge this optimistic view, suggesting that a benign catch-up requires that an inter-temporal budget constraint has to be taken into account.

By now, it is largely undisputed in the literature that the extent of external imbalances during the first decade of the Euro testified to inherent flaws of the currency union. Accordingly, the research focus shifted to the evaluation of the direction, composition, and drivers of capital flows and their effect on external imbalances.

Many studies have identified a core–periphery divide with respect to the direction of capital flows. Chen et al. (2013) find that countries in the eurozone's core financed current account deficits of peripheral countries by expanding inter-bank lending and purchasing public and private debt securities. Schmitz and Hagen (2011) argue that a similar direction of capital flows is also observable for the pre-Euro period, but that the common currency has increased the elasticity of capital flows with respect to per capita incomes.

A closer look at the composition of these flows reveals that they mainly mirror the increase in cross-country lending, which fueled domestic credit booms as reported by Giavazzi and Spaventa (2011) and Lane (2012). In accordance Chen et al. (2013) show how tremendously the French and German net foreign asset positions in debt securities against peripheral eurozone countries increased between 2001 and 2008. On the other hand, foreign direct investments within the eurozone decreased or stagnated, as found by Dinga and Dingová (2011) or Pantelidis et al. (2012).

Without doubt, the rise in financial capital flows can partly be attributed to a general financial deepening caused by the introduction of the Euro (Fernández-Villaverde et al., 2013). Apart from that, the logic of the Walters Critique (Walters, 1986) might explain the unsustainable scope of capital flows. Walters argues that the negative relationship between real interest rates and inflation rates within countries of a monetary union is likely to cause diverging and destabilizing business cycles. Following this logic, Angelini and Farina (2012) claim that low real interest rates in the peripheral countries spurred bank financing, domestic demand, and inflation. These findings also correspond to the persistence of country-specific inflation rates as recognized by Zemanek et al. (2010) or Altissimo et al. (2011).

Blanchard and Giavazzi (2002) note that the fall in nominal and real interest rates is a central point when explaining the appearance of macroeconomic imbalances in the eurozone. Using a model of inter-temporal optimization, they show how in theory an interest rate shock leads to lower savings, higher investments, and hence an increase in current account deficits. The overlapping generation models of Fagan and Gaspar (2007, 2008) are likewise capable of capturing a range of stylized facts observable in the eurozone. They show how an interest rate shock can trigger an increase in household expenditures and household debt levels and a deterioration of the current account. Nevertheless, Fagan and Gaspar (2008) conclude that these dynamics improve the welfare of all participants for all generations.

The rather positive assessment of current account imbalances by Blanchard and Giavazzi (2002) and Fagan and Gaspar (2007, 2008) is challenged by Giavazzi and Spaventa (2011) who noted that present current account deficits must be matched by future current account surpluses. For some countries in the eurozone's periphery they conclude that this solvency constraint was violated. Using a New-Keynesian framework, Carlin (2013) suspects that persistent and unsustainable current account deficits might be the result of non-rational wage-setters, who weakened the countries' competitiveness and prevented the self-stabilization of external imbalances. Collignon (2012) presumes that the prolonged period of low real interest rates might be responsible for a wage-setting hazardous for external competitiveness. Resorting to a simple static textbook model, Collignon (2012) illustrates how increasing wages and the accumulation of capital in southern eurozone countries shifted relative factor prices in the currency union and changed the competitiveness of member states. Angelini and Farina (2012) come to the conclusion that the financial deepening by means of the Euro did not promote macroeconomic convergence, but strengthened current and capital account imbalances across the eurozone.

This leads over to the second focus of this dissertation, which deals with regional growth structures and growth convergence across Europe.

The empirical convergence literature was unleashed by a pioneering paper of Baumol (1986), who established the concept of β-convergence. This measures the negative relationship between initial income and subsequent growth rates. Barro and Sala-i Martin (1992) and Mankiw et al. (1992) use different versions of the Solow model to formalize the concept of β-convergence. Their regression equations refer to the notion of conditional convergence, which states that convergence is conditional on similar structural characteristics. A corresponding panel specification is developed by Islam (1995). Besides cross-section or panel regression equations, Bernard and Durlauf (1995) propose a time-series framework, and Quah (1993) employs distributional dynamics to test for convergence.

Apart from conditional convergence, the notion of club convergence has gained importance in the empirical literature. According to the club convergence hypothesis, convergence to the same steady state growth path requires that the respective units' initial conditions are in the same 'basin of attraction' (Galor, 1996, p. 1056). In this respect, Azariadis and Drazen (1990) and Azariadis (1996) show how thresholds and increased returns to scale might lead to the emergence of multiple steady states.

A range of methods have been employed to test for the club convergence hypothesis. A regression tree analysis, where countries are first grouped according to initial conditions, is proposed by Durlauf and Johnson (1995). Hobijn and Franses (2000) develop a multivariate test for stationarity to identify convergence clubs. Canova (2004) uses initial conditions, geographic factors and threshold externalities as device to detect convergence clubs within a distributional framework.

More recently, Phillips and Sul (2007) developed a non-linear time-varying factor model for panel data, which takes unit-specific and transitional heterogeneity into account. In their study they also propose a regression-based test for convergence, the log t test as well as a club convergence clustering algorithm, which was later extended by a club merging rule (Phillips and Sul, 2009).

Various scholars, for instance Apergis et al. (2010); Fritsche and Kuzin (2011); Monfort et al. (2013); Borsi and Metiu (2015), have used the methodology proposed by Phillips and Sul (2007, 2009) to test for growth convergence in Europe on a national scale. For different time spans and panel sizes (including or excluding the new eastern European members of the EU), they find one to four convergence clubs in income per capita (income per worker). Moreover, in most of these studies a geographical pattern such as a north-south, east-west, or core-periphery division can be observed.

So far, only Bartkowska and Riedl (2012) have applied the Phillips and Sul (2007, 2009) methodology to assess growth convergence across European regions. In a panel of 206 NUTS-2 regions over the period 1990–2002, they identify six convergence clubs and a core-periphery division. Moreover, using an ordered logit regression which assesses the role of initial conditions for club membership, they confirm the validity of the club convergence hypothesis.

Nevertheless, a range of other methods have been employed to check for club convergence in European regions. The predictive density approach of Canova (2004) identifies four convergence clubs in a sample of 144 NUTS-2 regions between 1980–1992. Fischer and Stirböck (2006) use a spatial regression tree approach and find evidence of two spatial clubs in a sample of 256 NUTS-2 regions over the period 1995–2000. Ertur et al. (2006) apply a spatial regimes spatial error model on income data of 138 NUTS-1 and NUTS-2 regions over the period 1980–1995 and identify weak convergence in the southern regime and no convergence in the northern regime. A spatial Durbin model employed by Basile (2008) on a panel of 155 NUTS-2 regions over the period 1988–2000 identifies at least three convergence clubs and confirms the validity of the club convergence hypothesis with respect to initial income and schooling. In a panel of 255 NUTS-2 regions over the period 1991–2003, four convergence clubs, endogenously determined by Chow tests on cross-sectional regressions with a spatial error specification, are detected by Dall'Erba et al. (2008). Ramajo et al. (2008) control for regional heterogeneity before testing for β-convergence in a sample of 163 NUTS-2 regions over the period 1981–1996 and find that cohesion-fund countries constitute their own convergence club.

1.3 Strategy and Results

As mentioned above, the dissertation is divided into five studies. Two articles cover macroeconomic imbalances from a theoretical angle, and three articles are about income convergence from a methodological and empirical perspective.

Chapter 2 addresses the question whether converged nominal interest rates and persistent inflation differentials can be related to the emergence of unsustainable external imbalances in the eurozone. Although this issue has been extensively covered from different angles in the literature, a comprehensive explanation why capital flows within the eurozone were to a large extent not sustainable is still pending. The study suggests that imbalances can be explained by the fact that within a monetary union, the financial capital allocation mechanism for interest bearing capital is inefficient by nature. This inefficiency is caused by a discrepancy in the drivers of allocation: the supply side is driven by nominal returns and the demand side by real costs. If nominal returns (here: nominal interest rates) are equal across all countries of a monetary union, the demand for capital becomes the only effective driver for allocation. Moreover, due to the negative relationship between the country-specific real interest rate and inflation rate, capital flows are self-enforcing, pro-cyclical and ultimately inefficient. This defective capital allocation mechanism might explain why market forces did not prevent an unsustainable allocation of financial capital in the eurozone's first decade.

Apart from external imbalances, many eurozone countries experienced a shift in some of their macroeconomic parameters like consumption, investment, or income shares around the year the common currency was introduced. Chapter 3 assesses whether these developments can be linked to the simultaneous drop in real interest rates. Unlike previous works, which mostly employed models of inter-temporal optimization (Blanchard and Giavazzi, 2002; Fagan and Gaspar, 2007, 2008; Giavazzi and Spaventa, 2011), the study assesses the macroeconomic effects by using 'balances mechanics' as firstly proposed by Stützel (1958). A constant elasticity of substitution (CES) production function with capital and labor as inputs is incorporated into a system of income accounting identities. A comparative static analysis allows for the analysis of the effects of the interest rate shock on wages, income shares, overall saving and consumption rates, and the rate of foreign borrowing. It turns out that the signs of derivatives match the direction of macroeconomic changes observable in some eurozone countries. These results indicate that unsustainable macroeconomic developments in the eurozone's south can also be explained by a shock to a static system, without explicitly modeling rational or irrational consumers' behavior. From a methodological side, the approach illustrates that agent-specific saving rates and the elasticity of factor substitution are decisive to the model outcome. This finding calls for a reassessment of the predominant role of Cobb-Douglas specifications and single overall saving rates in economic modeling.

Chapter 4 is a methodological contribution to the clustering procedure proposed by Phillips and Sul (2007, 2009) (PS). The research question is whether the clustering of the PS (2007) algorithm can be refined, and whether a better clustering procedure is possible. A club merging algorithm is proposed, which is attached to the PS (2007) clustering algorithm and which formalizes the PS (2009) club merging rule. Furthermore, a novel hierarchical clustering algorithm based on the log t convergence test (PS 2007) is proposed. Results show that both the PS extension and the novel hierarchical clustering algorithm considerably improve the standard PS (2007; 2009) procedure. The hierarchical clustering algorithm outperforms the extended PS procedure if the underlying panel is more heterogeneous in the sense that it contains many clubs or diverging regions. On the other hand, the extended PS procedure performs better than the hierarchical clustering algorithm if the distance between clubs is narrow and in case of persistent transitional heterogeneity. Detailed recommendations as to which procedure should be employed for different panel sizes are provided as methodological guidelines for future empirical research.

Chapter 5 draws on the methodology tested in Chapter 4. The study is motivated by the observation that the parameters estimated in the PS (2007; 2009) procedure are very sensitive to the inclusion of further units. For example, a single additional unit might bring the club convergence speed from 20% down to zero. Therefore, a method is proposed that identifies the maximum number of clubs in a panel as well as the respective core regions of each club. The method, which is based on the hierarchical clustering algorithm introduced in Chapter 4, also allows for the identification of the most representative club convergence speed. The novel methodology is applied to a panel of income per capita data in 68 NUTS-1 regions over the period 1980–2011. Six club cores are identified, which merge to a total number of four clubs if the extended PS clustering procedure (cp. Chapter 4) is applied. A thorough investigation of club cores reveals that the speed of club convergence has decreased between 1998 and 2011. This decrease is caused by a fragmentation of existing clubs, indicating a rising importance of the concept of club convergence and pointing to an increase in regional heterogeneity across regions in the EU-15. The timing of trend changes suggests that cohesion policy has not been able to promote convergence across European regions.

The study in Chapter 6 is motivated by the question whether per capita incomes in European regions converge, or whether an economic division can be detected at this level, too. For this purpose, first the standard PS (2007) clustering algorithm is extended by a club merging algorithm (similar, but not identical to the one in Chapter 4), which formalizes the club merging rule recommended in PS (2009). Moreover, a merging algorithm for diverging regions is proposed to finalize club formation in case that regions formerly classified as diverging can be added to the newly composed clubs. The entire methodology is applied to per capita income data in a panel of 194 NUTS-2 regions over the period 1980–2011. Four convergence clubs are detected. Results of an ordered logit regression on the club membership, as proposed by Bartkowska and Riedl (2012), indicate that initial conditions matter for the resulting income distribution. Furthermore, geographical clustering is quite pronounced and points to a north-south division and a strong metropolitan effect.

1.4 Résumé

The proposition of Chapter 2, stating that a monetary union like the eurozone entails an inefficient real interest rate channel, is based on a very elementary and simple logic. Thus, the contribution of the study in Chapter 2 is the combination of three elements: first, a reflection on the interest rates driving capital demand and supply in a monetary union; second, a differentiation between interest-bearing and equity-based investments; and third, the recognition of the Walters Critique (Walters, 1986), implying a negative relationship between real interest rates and inflation rates. The resulting proposition is very fundamental. It reveals why the capital supply side - facing equal returns across the monetary union - was indifferent as to the recipient of their capital, thereby enabling a purely demand-driven capital allocation. Interestingly, the unconcerned behavior of the capital supply side was not even irrational as long as a burst of the growing credit bubble was well ahead. Whether the proposition of Chapter 2 can be empirically verified is an interesting question for further research.

The connection between Chapter 2 and 3 is very close, not least because both studies originate from the same initial draft. Given a demand-driven capital allocation as proposed in Chapter 2, Chapter 3 assesses how an economy reacts to a real interest rate shock. I abstained to employ a model of inter-temporal optimization for three reasons: first, the focus of the study is on the static effect of an interest rate shock on the whole economy, assuming that only firms react at all; second, a (rational) inter-temporal optimization was in my opinion not given in the context of eurozone capital flows; third, a heterodox approach referring to 'balances mechanics' might be found less sophisticated, but guarantees consistency in modeling and enables a better overview of macroeconomic effects. Findings illustrate that the chosen approach is well-suited to explain a range of macroeconomic developments in the eurozone without assuming rational or irrational behavior of households. Chapter 2 and 3 taken together show why and how a decrease in the real interest rate led to more capital inflows and the appearance of macroeconomic imbalances.

Chapters 2–3 carve out theoretical implications of macroeconomic imbalances in the eurozone. Chapters 4–6 address regional income growth patterns in the European Union from an empirical angle. These two issues are mutually related: macroeconomic imbalances and their potentially negative effects will certainly have an effect on growth, also at a regional level; vice versa, intrinsic differences like different average education levels to be found at the regional level are likely to influence overall macroeconomic performance.

Although not yet published, Chapter 4 is a potentially important contribution to the methodology proposed by Phillips and Sul (2007, 2009). The actual objective of the study was to conduct a Monte Carlo comparison of the PS (2007; 2009) procedure with a novel hierarchical clustering algorithm. For this purpose, the club merging rule (Phillips and Sul, 2009) had to be formalized. It turned out that the application of the proposed club merging algorithm not only formalizes the club merging rule (Phillips and Sul, 2009), but also considerably improves results compared to the standard PS (2007; 2009) procedure. In most cases, the new procedure (extended PS, or EPS) works best for high critical values c (cp. Step 3 in the clustering algorithm). Also, the hierarchical clustering algorithm is superior to the standard PS (2007; 2009) methodology, and it has certain strengths compared to the EPS procedure. As a side note, this study exemplifies how computational power reshapes modern economic research; the execution of all Monte Carlo simulations entailed the estimation of more than 70 billion OLS regressions (although this number is also owed to a Matlab coding, which could be more slender in some points).

Chapter 5 illustrates the practicability of the hierarchical clustering algorithm proposed in Chapter 4. The algorithm is used within a novel procedure proposed in this study, identifying the statistically most significant club members. The identification of these ‘club cores’ opens a range of possibilities for post-estimation analysis; in the context of this study it is illustrated how the speed of club convergence and the composition of clubs have evolved over time. Based on these results, it can be concluded that club convergence is not waning, but increasing in importance, thereby questioning the success of European regional policy.

The study in Chapter 6 is presented last in order to ensure a general-to-specific approach (here: from methodology in Chapter 4 to a NUTS-1 study in Chapter 5 to a NUTS-2 study in Chapter 6). The research agenda is similar to Bartkowska and Riedl (2012), but the study also features two methodological contributions and considers geographical factors in the ordered logit regression. Findings corroborate that club convergence is a relevant concept to explain regional growth patterns throughout Europe.

1.5 Reflections

Two main policy-relevant findings can be extracted from this dissertation: first, there is theoretical evidence that the capital allocation mechanism of the eurozone is intrinsically flawed, thereby enabling the appearance of hazardous macroeconomic imbalances; second, there is empirical evidence that growth patterns across Europe are driven by region-specific, potentially irrevocable features, which prevent absolute Europe-wide convergence. These two findings raise the question whether both the European currency union and European cohesion policy have been able and will be able to satisfy their own objectives.

An evaluation of this requires a short general reflection about the way European integration is and should be pursued. The basis is surely that, as declared in the Treaty on the European Union, the European integration aims to promote peace, social harmony, liberty, and economic well-being under the premise of democratic control and the rule of law (European Union, 1992). This clarifies that European integration is not an end in itself, but draws its ultimate legitimacy from the pursuance of certain objectives. A second point is that the relationship between the grade of integration and overall welfare is most probably not linear (apart from welfare being a multidimensional and subjective concept). Hence, 'the more, the merrier' as a guideline for European integration is as weak and simplistic as 'no integration'.

In the light of these considerations, the two central findings of this dissertation have two main policy implications. First, European and national policies should identify and strive towards an 'optimal level' of integration. In this respect, it is debatable whether the current political regime in Europe fulfills this criterion. The founding of the European currency union, for instance, was certainly well-intended; however, the inherent flaw identified in Chapter 2 as well as other issues which became visible during the Euro crisis indicate that the idea of a common currency union was actually premature. Claiming that Europe should strive towards the optimal integration level does not mean that certain levels of integration should or will never be achieved; given the dynamics of societies over time, the optimal level of integration will likewise change. The challenge for European politics is to keep the process of integration at the pace desired by its citizens and determined by its ultimate objectives.

The second policy implication is that, with view to a multi-speed Europe, national and European policy is requested to handle differences in a politically sensitive manner. In this context, the scope of political measures is limited by two border cases: either European policy employs measures which close differences by means of a transfer mechanism (full intervention); or European policy does not tackle existing differences at all (no intervention). A politically sensitive approach could imply that differences are conceded, but that each region or country is empowered to reach the highest possible growth path it can attain given its intrinsic limitations. Accordingly, public redistribution measures – besides being limited to a level accepted by the giving side –would only be taken if they enable countries or regions to enter a higher growth path in the long-run; they would not be used for a permanent transfer mechanism (except payments safeguarding subsistence).

These policy considerations are based on my belief that only an integration striving for its optimal level and accepting intrinsic differences will be a successful integration. If this principle is neglected, this might result in counteracting the aim of fostering peace and harmony across Europe. In this sense, well-intended is not always well-done. Moreover, supranational solidarity will turn into resentment and disharmony if it become a modus vivendi; experiences with fiscal transfers between the German Länder exemplify that this can occur even at a national level. As Keynes might have put it, “in the long run, a donor nation does not love its recipient”.

Finally, I would like to express my deep conviction that the political process of European integration will be overwhelmingly successful, if it accepts its intrinsic limitations and adjusts its pace to the necessities and beliefs of its citizens.

Chapter 2

Capital Allocation in a Monetary Union: Flows and Flaws

The appearance of macroeconomic imbalances in the eurozone and the outbreak of the euro crisis indicate that the allocation of financial capital within the monetary union was not efficient to a great extent after the introduction of the common currency. To identify the underlying explanations for flawed capital flows, this study considers the corresponding strands of the literature, revitalizes the so-called "Walters Critique," and combines both with basic macroeconomic theory. It is argued that in a monetary union such as the eurozone, the financial capital allocation mechanism for interest-bearing capital is inherently inefficient. This general proposition is derived from a fundamental discrepancy in the financial markets of a currency union, where the demand for interest-bearing capital is driven by real factors (real costs) and the supply by nominal factors (nominal interest rates). Given equal nominal interest rates across the member states of a currency union, the capital demand side is the only effective driver of financial capital. This allows for self-enforcing, pro-cyclical, and ultimately inefficient flows of financial capital. Anecdotal evidence of developments in the eurozone corroborates this theoretical explanation. The replacement of the eurozone's loose inflation and nominal interest rate criteria with a strict real interest rate convergence criterion is proposed as a policy implication.

JEL classification: E4, F3, F45, G1

Keywords: capital allocation, eurozone, interest rate, monetary union

[0] I would like to thank the participants at the 16th EBES conference for helpful comments. I also thank Edgar Baake, Ulrich Blum, Georg Koopmann, Thomas Straubhaar, and Rasmus Thoennessen for valuable comments on earlier drafts.

2.1 Introduction

This study addresses the question of how financial capital allocates within a monetary union such as the eurozone. According to neoclassical theory, capital is directed toward its most productive usage. By contrast, the present study argues that this logic only holds for equity-based investments in a monetary union (to the extent that investment decisions are based on business fundamentals). For interest-bearing financial capital interchanged on a supranational interbank market, an efficient allocation mechanism does not exist; instead, inefficient capital allocation prevails, which is conditioned by the nature of the currency union.

The following elaborations are motivated by economic developments observed before and after the European Monetary Union (EMU) came into effect. In the run-up to the euro, country-specific nominal interest rates converged to a unit eurozone level (e.g., see Fagan and Gaspar, 2008; Sinn, 2010; Fernández-Villaverde et al., 2013). However, inflation and thus real interest rate differentials persisted throughout the first years of the common currency (e.g., see Angeloni and Ehrmann, 2007; Zemanek et al., 2010; Altissimo et al., 2011). Moreover, massive capital flows occurred from the eurozone's core countries to the peripheral member states (e.g., see Schmitz and Hagen, 2011; Angelini and Farina, 2012; Chen et al., 2013). Capital was provided mostly via credit (e.g., see Giavazzi and Spaventa, 2011; Lane, 2012; Fernández-Villaverde et al., 2013), whereas *foreign direct investments* (*FDIs*) played only a minor role (e.g., see Dinga and Dingová, 2011; Aristotelous and Fountas, 2012; Pantelidis et al., 2012). These phenomena have all been addressed previously, but the very general and fundamental question remains about why a large quantity of financial capital within the eurozone was not allocated efficiently (as found at the outbreak of the euro crisis). The main contribution of the present study is the proposition of a fundamental and comprehensive theoretical explanation for these developments.

Briefly, the logic proposed in this study is as follows: foreign investments in equity are based on a discrete decision on the capital supply side. The expected real return on an equity investment depends on the business fundamentals, which in turn depend on the expected locally prevalent business environment. Hence, ex ante, the financial capital flows in equity are allocated efficiently (irrespective of whether efficiency also holds ex post). This logic holds for *FDIs* and for *portfolio equity investments* so far as (expected) equity prices are driven by (expected) business fundamentals.

By contrast, interest-bearing capital such as *portfolio debt investments* or cross-border loans subsumed under the item *other investment* is not provided on the basis of (expected) business fundamentals. The expected real return on this capital is determined by the prevailing nominal interest rates (which already incorporates expectations about future changes in the nominal interest rate), as well as by the expected inflation rate of the currency. For the capital demand side (ultimately, firms and consumers), real capital costs are given by country-specific real interest rates, which are determined by the overall nominal interest rates and the expected country-specific inflation rate. Therefore, capital demand is driven by real and capital supply by nominal factors, so an efficient allocation mechanism does not prevail. Even worse, given a unit nominal interest rate in a currency union, it makes no difference on the supply side where the capital eventually goes. Thus, capital demand is the only effective driver. Due to the negative correlation between country-specific real interest and inflation rates (Walters, 1986), the resulting financial capital flows will be self-enforcing, pro-cyclical, and hence potentially unsustainable. Therefore, the allocation of capital is not efficient; indeed, it is inherently inefficient. This general logic also holds in the presence of risk differentials, provided that risk premia are interpreted as a measure of compensation.

The reasoning outlined above builds on a distinct theoretical clarification of the following notions: 1) the relationship between a country's nominal and real interest rate and its inflation rate, 2) implications of different types of cross-country capital flows, and 3) an understanding of risk premia as a compensation tool. Previous studies (e.g., see Honohan and Leddin, 2006; Lane, 2011; Angelini and Farina, 2012) have recognized that country-specific real interest and inflation rates are negatively related within a monetary union, which was first suggested by Walters (1986) in the so-called "Walters Critique." Moreover, inefficiencies have been acknowledged in the allocation of supranational capital in the eurozone (e.g., see Angelini and Farina, 2012; Fernández-Villaverde et al., 2013). The present study extends this research and connects the negative relationship between inflation and real interest rates with the allocation of different types of supranational capital. Thus, a very general but fundamental inefficiency can be detected in the allocation of financial capital in a monetary union.

The remainder of this paper is organized as follows. Section 2.2 reviews different strands of the theoretical and empirical literature. Theoretical pre-considerations required to formulate the main argument are presented in Section 2.3. Subsequently, Sections 2.4 and 2.5 demonstrate how interest-bearing capital is allocated under monetary autonomy and in a currency union. Section 2.6 discusses the previous deliberations and draws on some empirical observations from the eurozone. Section 2.7 gives the conclusions of this study.

2.2 Literature review

The convergence in country-specific nominal interest rates during the run-up to the eurozone is widely acknowledged. Most previous studies have argued that improved financial conditions due to financial integration, the elimination of exchange rate risks, and the reduction of (perceived) country-specific risks led to this convergence (e.g., see Sinn, 2010, 2014; Fernández-Villaverde et al., 2013). More generally, in the (near) absence of country-specific risks, a unit nominal interest rate across members of a currency union is the logical outcome of nominal interest rate parity. Moreover, Honohan and Leddin (2006) argued that nominal interest rates become exogenous to the respective country through a supranational monetary policy; therefore, the law of one price holds for eurozone assets (Schmitz and Hagen, 2011), whereas the remaining nominal yield differences represent differences in risk and volatility (Lane, 2012).

The nominal interest rates converged to a unit eurozone level, but tight alignment of the inflation rates was never achieved across euro member states. Thus, López-Salido et al. (2005), Lane (2006), Angeloni and Ehrmann (2007), Zemanek et al. (2010), and Altissimo et al. (2011) noted substantially and persistently higher inflation rates on the eurozone's periphery. Given the economic heterogeneity within the currency union, these inflation differentials were not necessarily worrying: according to the Balassa-Samuelson effect (Balassa, 1964; Samuelson, 1964), low-income countries are likely to catch up in terms of economic growth and productivity, thereby exhibiting higher inflation rates. However, several studies, such as Honohan and Lane (2003), López-Salido et al. (2005), and Égert (2011), showed that the Balassa-Samuelson effect does not explain the extent and persistence of inflation differentials across the eurozone. Honohan and Lane (2003) reported that inflation differentials across a currency union are stronger than across the regions of a federal state due to low migration and a weaker fiscal system. López-Salido et al. (2005) identified aggregate demand shocks as the main driver of differences in inflation rates. Sinn and Wollmershäuser (2012) indicated that the inflationary bubbles in the peripheral euro member states were caused by loose credit conditions and the corresponding inflow of financial capital.

In addition to inflation differentials, the real interest rates have varied across the eurozone. In this respect, some researchers have referred back to the Walters Critique (Walters, 1986), which highlights the fact that country-specific inflation rates and country-specific real interest rates are inversely related within a monetary union. Honohan and Lane (2003) argued that high regional inflation rates automatically cause low regional real interest rates, thereby acting as a destabilizing force. They also found that country-specific real interest rates were negatively correlated before and after the EMU. The argument of the

Walters Critique was further emphasized by Honohan and Leddin (2006) who claimed that the exogenous nature of nominal interest rates within a monetary union leads to an inverse, pro-cyclical, and hence destabilizing relationship between country-specific real interest rates and inflation rates. In addition, Angeloni and Ehrmann (2007) and Angelini and Farina (2012) argued that low country-specific real interest rates spurred local demand in the eurozone. Other studies have also supported the Walters Critique (although not always explicitly), such as López-Salido et al. (2005), Lane (2006), and Lane (2011). By contrast, Mongelli and Wyplosz (2009) rejected the Walters Critique and argued that inflation rates did not diverge in the eurozone.

The unprecedented convergence in nominal interest rates can be treated as a substantial macroeconomic shock (e.g., see Honohan and Leddin, 2006; Lane, 2011), particularly for countries that were previously used to a loose monetary policy with high inflation and nominal interest rates. Causal relationships with other macroeconomic variables are difficult to prove, but the substantial changes in foreign economic patterns are likely to be related to the development of nominal and real interest rates. Various studies have highlighted an increasing disparity in current accounts across eurozone countries after the introduction of the common currency in 1999. Indeed, after the euro was introduced, core-to-periphery or north-to-south divisions in the current account balances were recognized by Arghyrou and Chortareas (2008), Lapavitsas et al. (2010), Schmitz and Hagen (2011), Angelini and Farina (2012), Bonatti and Fracasso (2013), Alessandrini et al. (2014), and Berger and Nitsch (2014). In particular, Chen et al. (2013) showed that current account deficits in the peripheral euro countries were financed by capital from the eurozone's core countries. A similar conclusion was reached by Schmitz and Hagen (2011), Angelini and Farina (2012), Fernández-Villaverde et al. (2013), Alessandrini et al. (2014), and Gros and Alcidi (2015).

In a seminal study, Blanchard and Giavazzi (2002) assessed the capital flow from relatively rich northern European countries to the relatively poor peripheral countries as a sign of economic catch up, and thus as evidence of a well-functioning currency union. Other researchers have also (partly) followed this line of reasoning. Abiad et al. (2009) argued that financial capital inflows have accelerated income growth in the poorer peripheral countries. However, as income convergence proceeds across countries, the "growth dividend" shrinks and so do the capital inflows. Schmitz and Hagen (2011) found that the EMU has increased the responsiveness of capital flows with respect to per capita income differences. Hence, the financial capital flows and income catch up observed in the eurozone confirm neoclassical growth theory. By contrast, later on Giavazzi argued that net capital flows to low income countries are indeed necessary for catching up, but that the intertemporal budget constraint was violated in the case of the eurozone (Giavazzi and Spaventa, 2011). Belke and Dreger (2013) suggested that income catch up does not fully explain the pattern of financial capital flows within the eurozone, but instead the real exchange rate is a more important determinant of the current account. Similarly, Angelini and Farina (2012) rejected a benign income catch-up process and highlighted the destabilizing effect of capital flows on the eurozone's periphery.

Regardless of the presence of catch up, economic theory (and common sense) predicts that financial capital should be allocated efficiently in the sense that it flows toward its most productive usage. This line of reasoning is also found in most studies of this issue, at least in the first years of the common currency. For example, Sinn and Koll (2000) predicted that the convergence in interest rates will allow capital to flow toward its most productive usage, thereby boosting growth. Moreover, Baele et al. (2004), Lane (2006), Fernández de Guevara, Juan et al. (2007), and Schmitz and Hagen (2011) all argued that financial integration, as implied by a common currency, facilitates or has facilitated the efficient allocation of capital. However, Fernández-Villaverde et al. (2013) claimed that the financial bubble observed in the eurozone makes it difficult to assess the efficiency of investment. In general, the financial turmoil in the eurozone may be an overwhelming indication that the allocation of financial capital within the eurozone was not efficient, but instead it was destabilizing.

In this context, it may be necessary to look more closely at the nature of financial capital flows. Many studies (e.g., see Lane, 2006, 2012; Giavazzi and Spaventa, 2011; Angelini and Farina, 2012; Fernández-Villaverde et al., 2013; Sinn, 2014; Gros and Alcidi, 2015) have mentioned or reported domestic credit booms on the periphery. These credit booms were financed via the European interbank market, which also experienced a massive increase in lending after the euro's introduction (e.g., see Lane, 2006; Giavazzi and Spaventa, 2011; Chen et al., 2013). By contrast, net *FDIs* in the periphery stagnated or even decreased, as suggested by Jaumotte and Sodsriwiboon (2010) and shown by Dinga and Dingová (2011) and Aristotelous and Fountas (2012). Pantelidis et al. (2012) even found a negative effect of EMU on *FDIs* in Greece, Portugal, France, Belgium, and Spain. Chen et al. (2013) showed that there was a tremendous increase in the net foreign asset positions of France and Germany with respect to eurozone debtor countries between 2001 and 2008. They also found that nearly all of the net assets were debt securities, whereas claims on *FDIs* and *portfolio equity investments* were negligibly small. In summary, capital flows toward the periphery mainly financed credit bubbles rather than being attracted by the real economy. In this background it is highly questionable whether the allocation of financial capital in the eurozone was efficient.

Therefore, the question arises of why no adjustment mechanism was in place in the eurozone to offset future imbalances. It is widely considered that an appreciation of the real exchange rate will offset the demand-boosting effect of a low real interest rate (e.g., see Angeloni and Ehrmann, 2007; Mongelli and Wyplosz, 2009). Moreover, Abiad et al. (2009) predicted that capital inflows are self-limiting and transitory because they shrink the growth dividend obtained from investing in a specific country. By contrast, Chen et al. (2013) recognized that real exchange adjustment mechanisms did not work after the eurozone was implemented. One reason for the weakened adjustment mechanism was the restricted means of fiscal policy as a (supra-) national policy tool, which was recognized by Honohan and Lane (2003) and Alessandrini et al. (2014). In Spain, López-Salido et al. (2005) showed that self-correction of inflation differentials was weak. They also emphasize the role of wage rigidities in hindering real adjustment.

Obviously, there have been many previous studies of this topic. However, although inefficiencies have been noted in the allocation of financial capital in the eurozone, a coherent and comprehensive theoretical explanation of this issue is still required. Therefore, in this study, a fundamental theoretical explanation is proposed for how financial capital is allocated in a monetary union.

2.3 Theoretical Pre-considerations

Several theoretical clarifications are necessary in order to formulate the argument presented in this study. If not indicated differently, general reflections formulated in this and the following two Sections (2.4 and 2.5) are based on own considerations.

First, the terms capital demand and capital supply used throughout this study are not common in the finance literature, which usually refers to supply and demand in asset markets in order to determine the prevailing interest rates (Mishkin, 2010, Chapter 5). The focus of this study, however, is not on the determination of interest rates, but on the supranational allocation of a finite amount of financial capital. This allocation is driven by supply and demand side factors: the capital owners on the supply side search for the place where their capital generates the highest real return, whereas the capital demand side wants to finance either consumption or investments as cheap as possible. In this context, postulating a demand or supply for assets is misleading, since it implies that these assets already exist. This paper looks at the preceding return and cost considerations (as just mentioned) and aims to explain how capital allocates across countries. Thus, it uses the notions of capital demand and supply.

The second point refers to the exogeneity and endogeneity of the overall and country-specific levels of interest rates. Under monetary autonomy, a country is able to conduct its own monetary policy to achieve a certain nominal interest rate. Hence, nominal interest rates are determined endogenously by the country. By contrast, real interest rates as a measure of the increase in real purchasing power are determined exogenously by the real conditions and real growth expectations. Following the Fisher equation, the residual element is the expected inflation rate, which is determined by three effects: monetary policy has a long-run effect on inflation, following the law of "money neutrality" as first recognized by Hume (1752); rising productivity described by the Balassa-Samuelson effect (Balassa, 1964; Samuelson, 1964) has a medium-term impact; and inflationary gaps play important roles in the short run (Keynes, 1940). If we assume that fiscal policy measures have no effect on productivity and growth, then inflation can be defined as partly endogenous because of the long-run effect of monetary policy.

In a currency union, the nominal interest rate is imposed exogenously on a country by a supranational monetary regime (Honohan and Leddin, 2006). The inflation rate within a country is still explained by both monetary and real determinants, but the difference is that monetary inflation is now imposed exogenously by a supranational policy. Under the assumption of ineffective fiscal policy, the inflation rate is now purely exogenous for the country. (The assumption of an effective fiscal policy would weaken this exogeneity, since this implies that demand- and productivity-driven inflation can partly be governed.) Country-specific real interest rates continue to measure the increase in real purchasing power, but they now act as the residual of exogenous rates of nominal interest and inflation. This mutuality of country-specific real interest and inflation rates within a monetary union was first recognized by Walters Walters (1986) in the so-called "Walters Critique."

Based on the mutuality of real interest and inflation rates in member states of a monetary union, it follows that the real interest rate channel might have a destabilizing effect. A comparably low real interest rate increases the demand for capital within a specific country, where the resulting increase in financial capital inflows further decreases the real interest rate and inflation increases in an analogous manner. The reinforcing real interest rate effect is associated with a pro-cyclical effect on the real economy. This logic has been acknowledged in some previous studies (e.g., see Honohan and Lane, 2003; López-Salido et al., 2005; Honohan and Leddin, 2006; Lane, 2006; 2011; Angeloni and Ehrmann, 2007; Mongelli and Wyplosz, 2009; Angelini and Farina, 2012), but the implications of the Walters Critique for the allocation of supranational capital still need to be considered in depth.

A third clarification is necessary in terms of the nature of financial capital flows. In the financial account of an economy, capital flows are sub-classified into *FDIs*, *portfolio investments*, *other investments*, and the *reserve account* (not treated here). In addition, these flows can be classified methodologically according to the nature of their returns, where they either generate income on equity (dividends, distributed and undistributed profits, and reinvested earnings) or income on debt (interest). Both types of income have very different implications.

Ex ante, the expected real return on foreign equity is given by the expected real increase in the value of the respective equity asset (regardless of whether this increase in value is distributed or retained). Thus, foreign equity investments are based on a discrete decision by an investor or a company, which transforms a certain amount of financial capital into equity in order to realize an expected real return on income. The investment will be conducted provided that the "individual" expected real return, which is generated locally by the development of the operational business, exceeds the equivalent expected real interest rate that prevails on the respective financial markets. This logic follows the efficient-market hypothesis, which is based on the condition that arbitrage eventually removes all unexploited profit opportunities, thereby equalizing real returns of equivalent assets (for an overview of the efficient-market hypothesis, cp. Mishkin, 2010, Chapter 7). The investment decision is discrete in nature and it follows real returns based on expected local business fundamentals, so the capital allocation is efficient ex ante (i.e., at the time of the investment). This logic holds regardless of whether the investment decision is efficient ex post.

A foreign debt investment generates interest income. Ex ante, this will be conducted provided that the expected real return exceeds a reference expected real interest rate that prevails on the respective financial markets. Under normal circumstances, the debtor that offers the highest expected real interest rate is selected by the creditor, which ensures the real interest parity condition, thereby leading to an efficient allocation of financial capital.

FDIs are typically equity investments (excluding interest on inter-company debt), whereas *other investments* are mainly debt securities (deposits, trade credits, and bank loans). *Portfolio investments* are divided into investments in equity (such as stocks) and debt (bonds, notes, money market instruments, and financial derivatives) (European Union, 2005). Under monetary autonomy, both foreign equity and debt investments imply an efficient allocation of capital. In the following sections, it is argued that this efficiency is not obtained for debt investments in a monetary union.

Finally, it is necessary to discuss the notion of risk. Let us assume that two companies A and B ask for a loan from a representative bank. Company A virtually has no risk, whereas there is a certain likelihood of default for company B. Therefore, company B must pay an additional risk premium, so the expected real return from both loans is equal for the bank. If the representative bank is risk neutral, it would be indifferent when providing either A or B with the loan. For the case of risk affinity, the bank would prefer to give the loan to B, thereby hoping to realize a higher real return. However, company B may anticipate the risk affinity of the bank and squeeze the risk premium near to the point where the bank is indifferent between A and B. In turn, the risk premia are increased close to the indifference point in the case of risk aversion.

The size of the risk premium and its determinants (the actual expected risk and the risk attitude) will certainly have an effect on the volume of credit given to risky and non-risky business ventures. For example, decreased risk premia due to growing risk affinity increases the amount of risky investments that become profitable and thus that are financed. Moreover, other factors certainly influence financial capital flows, such as improved expectations in boom times or an overall ex-ante mis-assessment of the risk and profitability. However, the prevalent risk premium in the market still makes the representative investor indifferent between a risky venture and a non-risky equivalent. Thus, throughout this paper risk premia are treated as a measure of compensation and not as part of the real return. Following this, the introduction of risk does not affect the general logic of the considerations addressed in the following sections.

2.4 Capital Allocation under Monetary Autonomy

In an economic coalition among countries, where each country has its own currency and monetary policy, an efficient allocation of financial capital prevails in the presence of perfect capital mobility. The demand for capital is driven by real capital costs and the supply by real returns. All else equal, the demand for (supply of) capital is higher for low (high) real interest rates and lower for high (low) real interest rates. With perfect capital mobility, this will eventually lead to a real interest rate convergence process across countries, which should be accompanied by an efficient allocation of financial capital.

Figure 2.1 illustrates this logic for two countries, i.e., *home* and *foreign*, under the assumption of perfect capital mobility and no differences in risk. Competition in capital markets guarantees that all of the financial capital will be "employed" and that the real costs of capital, i.e., the country-specific real interest rate, equal its marginal product. The final capital allocation lies at point C, where the real interest rates (i.e., MPC and MPC^*) of both countries are equalized. If the expected country-specific inflation rates differ (as assumed in Figure 2.1), then the nominal interest rates i and i^* also differ. This logic follows the real interest rate parity condition, where the expected nominal returns between two investments in two countries will lead to the same expected real return due to expected adjustments in the nominal exchange rate.

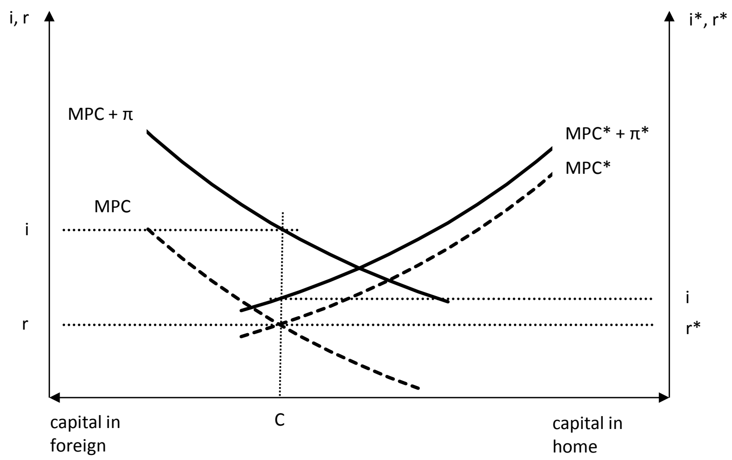

Fig. 2.1: Interest rates and capital allocation in an economic coalition. Assumptions: *home* and *foreign* are identical except for inflation rates and there is perfect capital mobility between *home* and *foreign*. Source: own illustration based on (Baldwin and Wyplosz, 2012, p. 500).

2.5 Capital Allocation in a Monetary Union

The logic outlined in the previous section also holds within a monetary union, but only for investments in equity. In this case, investors must consider the locally prevailing revenue and cost structure, which determines the locally prevailing expected real return. For example, the expected real return of a direct investment in a foreign company comprises the additional and locally generated expected real profit; therefore, a foreign equity investment will only occur if the expected real return exceeds an equivalent expected real return on the capital markets of the monetary union.

An efficient financial capital allocation is not given for interest-bearing investments within a monetary union. This is mainly due to the calculation of the expected real returns on debt investments. Given an exogenous nominal interest rate (set by the supranational monetary authority), the expected real return for the supranational-operating capital supply side is equal across the monetary union. It is simply the nominal interest rate (which already incorporates expectations) minus the expected average decrease in purchasing power of the underlying currency, i.e., the expected *average* inflation rate across the union. By contrast, under monetary autonomy, the expected real return on a foreign debt investment is calculated using the expected *country-specific* inflation rate.

For debt investments in a monetary union, it follows that a higher nominal interest rate also gives a higher real return. Therefore, the supply of financial capital is driven by country-specific *nominal* interest rates. By contrast, financial capital demand is driven by country-specific *real* interest rates because these rates are the locally prevalent real costs of capital for consumers and firms. Thus, the efficient allocation of financial capital is clearly not guaranteed due to the different drivers on the supply and demand sides.

Given that debt investments are driven by nominal interest rates and given that the nominal interest rates are equal across countries, then the supply side channel does not even operate and capital demand becomes the only effective allocation driver. The country-specific real interest and inflation rates are negatively correlated, so the financial capital flows will be self-enforcing, pro-cyclical, and hence unsustainable. Overall, the allocation of financial capital will not be efficient; indeed, it is inherently inefficient.

Figure 2.2 illustrates this logic based on a comparison with the efficient allocation under monetary autonomy shown in Figure 2.1. The final capital allocation lies at point C', where the nominal interest rates (i.e., $MPC + \pi$ and $MPC^* + \pi^*$) and the union's average marginal productivity are equal for the countries *home* and *foreign*. At this allocation point, the country-specific inflation differentials generate a larger marginal productivity from capital in $foreign$ compared with *home*. This is accompanied by a higher real interest rate $r^{*\prime}$ in $foreign$ compared with the real interest rate r' in *home*. Moreover, the capital allocation between *home* and $foreign$ deviates from its efficient point C, which is given by equal real interest rates (i.e., equal marginal products).

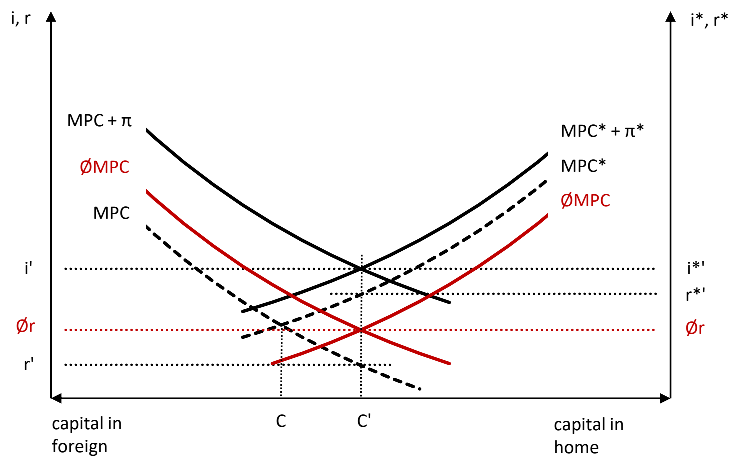

Fig. 2.2: Interest rates and capital allocation in a monetary union. Assumptions: *home* and *foreign* are identical except for inflation rates and there is perfect capital mobility between *home* and *foreign*. Source: own illustration.

As mentioned above, this logic is not changed by the introduction of risk. At the time of an investment within a monetary union, the risk premium assigned to any country by capital markets is a perfect compensation for the actual and expected risk based on a consideration of the representatives investor's risk attitude. Hence, the representative investor obtains an equal benefit from a risky or non-risky investment, and thus even in the presence of differentiating nominal interest rates due to risk, there is no mechanism that drives the investor to provide financial capital to the most productive investments (given by the investment with the highest risk-adjusted real interest rate). Again, this does not exclude the possibility that a change in the risk premium affects the financial capital flows; thus, when the country-specific risk premium is higher, fewer debt-financed investments are profitable in that country, so the demand for capital is lower and the amount of financial capital inflow is lower. In addition, the logic of the proposition is not affected by an incorrect risk assessment: it does not make a difference ex ante whether a risk was assessed wrongly ex post.

2.6 Discussion

As demonstrated in Section 2.2, previous studies have addressed a wide range of macroeconomic developments that occurred in the first decade of the eurozone. However, a coherent theoretical explanation for the appearance of imbalances has not been formulated previously. Therefore, the present study assembles the (empirical) evidence, revitalizes the Walters Critique (Walters, 1986), and combines both with simple macroeconomic theory and logic. The result is a potential theoretical explanation for the macroeconomic imbalances in the eurozone, thereby highlighting the inherent conceptual flaws embodied in a supranational monetary union.

The logic outlined above contrasts with standard academic explanations of macroeconomic imbalances in the eurozone (cp. Section 2.2). The increase in cross-border capital flows within the eurozone has often been interpreted as a sign of financial market integration (e.g., see Spiegel, 2009; Schmitz and Hagen, 2011). However, while more closely integrated financial markets will certainly ease financial capital flows, this does not explain the blatant lack of sustainability for these flows. Similarly, decreasing risk differentials might explain the increase, but not the unsustainable volume of capital inflows. In this sense, the logic outlined above does not exclude any previous explanations of increased financial capital flows, but it does explain their obviously unsustainable scope.

A major component of the reasoning detailed above is that the capital supply side of interest-bearing investments is driven by the overall nominal rates and not by country-specific real interest rates. This is because the real return of a supranational money investment is calculated using the inflation rate of the currency, which is equal across the union. This fact has not been addressed in recent studies, although in the past, Neumeyer (1998) acknowledged that a supranational common currency equalizes the real returns across the union.

A basic consideration of some macroeconomic developments in the eurozone might corroborate the overall theoretical argument. For the eurozone and some selected members, Figure 2.3 illustrates the development of country-specific short-term nominal and real interest rates, and the rates of net lending/borrowing with respect to the rest of the world. The time horizon was selected in order to cover the run-up period (between the Treaty of Maastricht in 1992 and the introduction of the euro in 1999) with an operation period of equal length (from 1999 to 2006). Evidently, nominal interest rates converged in the run up to the euro and they remained at a unit level from the time of its introduction (Panel A). Real interest rates declined in the eurozone and in all of the selected countries except Germany (Panel B). Up to the end of the run-up period, the real rates in Italy, Spain, and Portugal fell below the eurozone average, and they remained below the average in the operation period. Greece followed two years later when it joined the currency union. By contrast, the real interest rate in Germany switched from being below the eurozone average to above it. Panel C in Figure 2.3 illustrates that net borrowing grew in the eurozone's periphery, whereas Germany became a substantial net lender of capital. In a similar manner, we could depict the current account in order to represent imbalances on the real side.

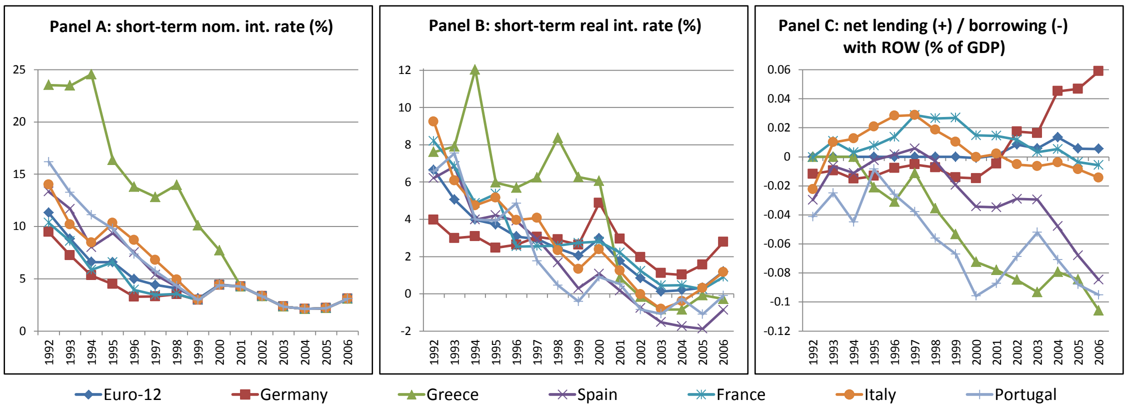

Fig. 2.3: Interest rates on public debt and capital accounts in the eurozone and selected countries. The short-term real interest rate was derived ex post by subtracting the country-specific inflation rate from the short-term nominal interest rate. Data source: AMECO.

In previous economic studies, it has been proposed that the capital account imbalances illustrated in Panel C can be explained by various desirable or undesirable factors, such as catch-up processes, financial market integration, mis-pricing, or over-optimism (Section 2.2). In this study, it is argued that a currency union such as the eurozone is inherently flawed because no efficient financial capital allocation mechanism exists for debt investments within the monetary union. To illustrate this point, Figure 2.4 subdivides the net international investment positions of Greece, Portugal, and Germany into their main components, where the time span covers the first decade of the common currency.

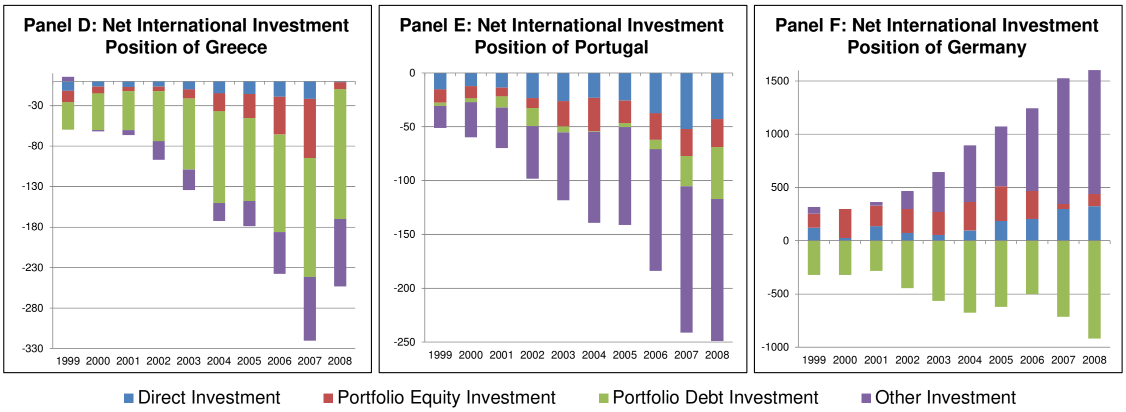

Fig. 2.4: Composition of the net international investment positions of selected countries (in billions of Euros). Data source: IMF.

Greece and Portugal had a negative balance in all of their investment positions throughout this period, whereas only Germany's *portfolio debt investments* position was negative. Direct investment played a negligible role in Greece and a minor role in Portugal and Germany. The stock of net *portfolio equity investments* remained fairly stable in Portugal and Germany, whereas it became substantially negative in Greece. Greece also experienced a tremendous negative increase in its net stock of *portfolio debt investments*, whereas this deterioration was less pronounced in Germany and patchy in Portugal. The net positions in terms of *other investments* were negligibly small in 1999, but they diverged greatly throughout the decade. Thus, Greece's initially balanced stock became a major negative. By 2008, more than half of the Portuguese negative net investment position was covered by *other investments*. By contrast, *other investments* comprised nearly three-quarters of Germany's positive net investment stock.

The data shown in Figure 2.4 do not consider bilateral developments within the eurozone, and thus they are potentially biased by international financial capital flows toward the eurozone (for an investigation of bilateral capital flows, compare Waysand et al., 2010). However, Chen et al. (2013) showed that the current account deficits in the European periphery were financed mostly by intra-eurozone capital flows. Moreover, Hale and Obstfeld (2014) found evidence that core eurozone countries increased their international borrowing and their lending to the periphery, which might explain Germany's negative net position in terms of *portfolio debt investments* and its positive one in terms of *other investments*. Regardless, the tremendous negative increase in the net stock of debt securities in Greece and Portugal, and the growth of outstanding *other investments* in Germany are very distinct. Given that the lack of sustainability for these capital flows was confirmed by the subsequent euro crisis, these developments corroborate the theoretical argument given above that interest-bearing capital lacked an efficient allocation mechanism. A thorough empirical verification of this anecdotal evidence is left for further research.

Basically, every country that has its own currency constitutes a currency union. Thus, the proposition that debt investment in a currency union lacks an efficient allocation mechanism also holds within every country with monetary sovereignty. However, several mechanisms may guarantee an efficient allocation or prevent an inefficient allocation. The regional markets within a country are tightly intertwined and they usually face the same overall business cycle (which need not hold within a monetary union of different countries). Hence, inflation differentials are less likely to appear between regions, but if they do, market forces that ensure a rapid adjustment are stronger because goods and factors are more mobile, and goods are closer substitutes within a country rather than across countries. From the public financial side, fiscal transfers will prevent or correct economic imbalances between different regions within a country.

By contrast, in a supranational currency union such as the eurozone, regional boom-bust cycles are more likely, more pronounced, and more destructive due to the pro-cyclical real interest rate channel, as described in the Walters Critique (Walters, 1986). Moreover, fiscal policy tools are rarely available and market correcting mechanisms are weak. Overall, such a monetary union is more likely to be accompanied by the inefficient allocation of financial capital, thereby leading to the appearance of unsustainable macroeconomic imbalances. Therefore, the development and convergence of real interest rates becomes the ultimate criterion for testing whether a monetary union is viable.

At present, a country that wants to join the eurozone must have a nominal interest rate level that differs by less than 2 percentage points and an inflation rate by less than 1.5 percentage points compared with the EU's three lowest inflation countries (European Union, 1992). Given the proposition described above, these requirements seem to be slack because a substantially different real interest rate level and substantially different real conditions are possible compared with the eurozone's average. Moreover, after admission to the eurozone, no incentive-compatible policy tool is in place to ensure convergence in terms of either the country-specific inflation or real interest rates. A more rewarding and sensible policy would be a single requirement, which demands similar real interest rates for a specific time period before admittance paired with a "business plan" that sets out potential measures to ensure similar real interest rates after admittance. This principle of achieving convergence in terms of real interest rates should also lead European policy makers during the current euro crisis.

2.7 Conclusion

The present theoretical study provides a potential theoretical explanation for why the allocation of financial capital in the first decade of the eurozone was mainly inefficient. This hypothesis also explains why low or even decreasing country-specific real interest rates in the eurozone were accompanied by increasing capital inflows, which is a fact that contradicts neoclassical expectations.

The study shows that in a monetary union, the supply of interest-bearing capital is driven by the overall nominal returns rather than by country-specific real rates. This is because the nominal return on any money investment within a monetary union is deflated by the *average* inflation rate. The demand for capital is driven by the country-specific real capital cost, which is given by the respective real interest rate, so the drivers of capital demand and supply differ. Therefore, there is no efficient capital allocation mechanism for interest-bearing capital, where the self-enforcing and pro-cyclical mechanism described in the Walters Critique (Walters, 1986) even leads to inefficient allocation. Hence, the financial capital flows within a monetary union are inherently likely to be flawed, thereby establishing unsustainable macroeconomic imbalances. This logic is not affected by the actual and perceived risk, and the risk attitude, although both will eventually influence the volume of financial capital flows.

Previous studies have extensively investigated capital flows and macroeconomic imbalances from both theoretical and empirical perspectives. However, no coherent and comprehensive theoretical explanation for the unsustainability of financial capital flows has been formulated previously, which is the main contribution of the present study. To obtain this explanation, the corresponding strands from the literature were assembled, the Walters Critique was revitalized, and the implications of both were combined with standard macroeconomic theory. Anecdotal evidence of developments in the eurozone corroborates the proposed theoretical explanation.

The nominal interest and inflation rate criteria for eurozone accession (European Union, 1992) allow persistent cross-country real interest rate differentials. However, given the theoretical implications of the present study, the strict convergence of real interest rates is essential for the efficient allocation of financial capital, and thus for the viability of a currency union. Therefore, it is suggested as a policy recommendation that the eurozone's loose inflation and nominal interest rate requirements should be replaced by a strict real interest rate convergence criterion.

Further research in this area may address several issues. The Walters Critique requires a deeper theoretical exploration and a thorough consideration based on the empirical literature. Moreover, an empirical verification of the present study's theoretical reasoning is required. Thus, a closer look at the drivers of interest-bearing (bilateral) capital flows in the eurozone might yield important insights.

Chapter 3

Macroeconomic Effects of Interest Rate Convergence

This study investigated the macroeconomic effects of an exogenous drop in real interest rates from a theoretical perspective. In particular, this study was motivated by developments observed in southern European countries during the years around the introduction of the Euro. A constant elasticity of substitution production function was used to model the effects of a drop in real interest rates on the production side of an economy. Labor input and the profit income share were set as exogenous factors, thereby allowing the endogenization of wages and output. This micro-foundation was subsequently incorporated into a system of national income accounting identities. A comparative static analysis of the model showed that the sign of macroeconomic changes observed over several years in some eurozone countries could potentially be explained by a real interest rate shock and the corresponding effects through "balances mechanics." This result rejects the hypothesis that macroeconomic imbalances are caused mainly by irrational or irresponsible consumption behavior. The model shows that both the elasticity of factor substitution and agent-specific saving rates play pivotal roles in the theoretical explanation of macroeconomic imbalances.

JEL classification: E00, F41, F32, F45,

Keywords: balances mechanics, eurozone, income accounting, macroeconomic imbalance, real interest rate

Subtitle: A Micro-Founded Income Accounting Approach

[0] I would like to thank the participants at the 16th EBES conference for helpful comments. I also thank Georg Koopmann, Thomas Straubhaar, and Rasmus Thoennessen for valuable comments on earlier drafts.

3.1 Introduction

The public discussion of the introduction of the Euro and the reasons for the Euro crisis is often characterized by subjective concerns about the behavior of economic agents in some member states, where irresponsible or unsustainable economic behavior is identified as a key cause of the appearance of macroeconomic imbalances. These claims might be justified in some cases, but they obscure the fact that imbalances can also be caused by the passivity of economic agents. Given that the introduction of the common currency comprised an exogenous shock of an unprecedented extent for many of the joining countries (Lane, 2011), then macroeconomic imbalances should have been expected if behavioral adjustments were delayed or avoided. Thus, major economic developments can be explained partly by the absence of any discrete change in the consumption behavior of economic agents.

The present study provides new theoretical insights into the non-behavioral economic relationships and causal effects of income accounting mechanisms in two main respects. First, in terms of methodology, a heterodox framework is proposed that combines a cost-minimizing constant elasticity of substitution (CES) economy (micro-foundation) with a system of income accounting identities (macro-integration). This process allows the derivation of theoretical relationships under the premise of macroeconomic consistency. Second, using the proposed comparative-static framework, it is shown that the major macroeconomic developments in southern European countries can also be explained by "balances mechanics," without changing the consumption behavior of the economic agents in any direction.

In economic research, the most common theoretical approach for explaining macroeconomic imbalances is the use of a model of inter-temporal optimization. For example, Blanchard and Giavazzi (2002) employed an open-economy model where households live for two periods and maximize the utility according to an inter-temporal budget constraint. The effect of goods markets and financial integration is a higher elasticity of demand for domestic goods and a lower consumption interest rate. In borrower countries, this leads to lower savings and higher investments, thereby widening the current account deficits as a side-effect of economic catch-up. However, Giavazzi, has now argued that in a currency union, countries also have to satisfy an inter-temporal budget constraint, which guarantees that the present current account deficits are matched by the present value of future surpluses (Giavazzi and Spaventa, 2011). If foreign capital is invested in the non-tradable sector, as occurred in Ireland and Spain, then the solvency constraint is violated.

Similarly, Fagan and Gaspar (2007, 2008) proposed an overlapping generations model where households maximize their present (discounted) utility for consuming a traded and non-traded good subject to an inter-temporal budget constraint. The economy's endowment with both goods is given exogenously; therefore, the effects of sectoral production shifts with respect to an inter-temporal solvency constraint are ignored. Nevertheless, their model could capture a range of the main macroeconomic developments in the first decade of the eurozone. Using a similar framework, Koronowski (2009) showed that a monetary union's simultaneous exchange and interest rate restrictions cause the emergence of diverging business cycles because the individual micro-optimization of consumers does not lead to a macroeconomic equilibrium.

The development of wages is of pivotal importance for macroeconomic imbalances in the eurozone. Carlin (2013) showed how a standard New Keynesian framework fails to achieve self-stabilization of shocks if wage setting is not rational. Rational wage setting would ensure parity of real interest and real exchange rates across member states of a currency union. By contrast, in the eurozone, a mix of rational and non-rational wage setters led to country-specific inflation differentials and unbolted a destabilizing real exchange rate channel, as described in the critique by Walters' (1986). In this context, Collignon (2012) argued that the "Golden Rule" in wage setting was not appropriate for the eurozone: it led to stable profit margins of firms, but it did not react to the drop in capital productivity at the periphery of the eurozone. Thus, the drop in real interest rates in some eurozone countries eventually caused divergence in their relative cost competitiveness.

The present study differs from previous investigations that have explained macroeconomic imbalances in the eurozone by solving an infinite-horizon or overlapping generations model. Instead, the starting point of this method is an open economy, which is assembled with the CES technique using labor and capital as factor inputs. This micro-foundation is embedded into a system with three income accounting identities (macro-integration). Subsequently, it is shown how a ceteris paribus drop in the real interest rate affects a range of variables, including output, consumption, wages, savings, and the distribution of income. There are two main assumptions about behavior: the CES economy minimizes costs and reacts to a change in the price of capital, but the consumption behavior of the economic agents does not adjust, where the latter facilitates the separation of the non-behavioral effects of an interest rate shock.

The approach employed in this study was inspired by a model used in Collignon (2012, p. 75). The execution of this model follows the logic of "balances mechanics" ('Saldenmechanik'), as proposed in the German economic literature by Stützel (1958). Stützel noted the presence of absolute economic relationships that always hold. These relationships are based on the logic of income accounting, where any additional revenue causes an equivalent additional expenditure somewhere else. The consideration of "balances mechanics" prevents the mixing of globally and partially holding relationship during the construction of economic models. Hence, despite their "trivial arithmetic" nature, they can be seen as making a useful contribution to economic theory, as argued by Schmidt (2011).

In the present study, "balances mechanics" are considered by integrating a micro-model into three national income accounting identities. Moreover, to consider partial deviations from global developments, saving rates are allowed to differ across different agents. Few studies have employed similar approaches, but the exceptions include Helmedag (2008), who investigated the distributional dynamics of changes in overall investments, Hayes (2010) and Lindner (2012), who used accounting identities to investigate the loanable funds theory, and Schmidt (2011), who generally re-viewed "balances mechanics." In addition, there are conceptual similarities with the "stock-flow consistent models" proposed in the Post-Keynesian literature (particularly, Godley and Lavoie, 2007).

The reminder of this paper is organized as follows. Section 3.2.1 describes the evolution of the macroeconomic data, which is considered in the theoretical approach. The model setup (micro- and macro-) is explained in Sections 3.2.2 and 3.2.3, which is followed by the comparative statics analysis in Section 3.2.4. Section 3.2.5 describes the procedure and presents the results, while Section 3.2.6 considers the (policy) implications of these results. Concluding remarks are given in Section 3.3.

3.2 A Micro-Founded Income Accounting Approach

3.2.1 Some Data

The theoretical examination in the following is motivated by developments in macroeconomic variables in the run-up to the eurozone and during the first decade of the Euro. Figures 3.1 to 3.3 illustrate the corresponding developments in the eurozone on average, in Germany, and in the so-called GIPS countries (Greece, Italy, Portugal, and Spain). The time period considered starts from 1992, which is the year when the Maastricht Treaty was signed, and ends in 2006, which was the year before the global financial crisis began. Hence, the data comprise a range of seven years around the year 1999 when the Euro was introduced in all of the countries under consideration (except Greece, which followed in 2001). The data were taken from the European Commission's AMECO database. Due to reasons concerning data availability and consistency, the index for the labor income share was calculated using International Monetary Fund (IMF) data until the year 1995.

Some of the developments presented in Figures 3.1 to 3.3 have been widely acknowledged and investigated in previous studies, as discussed in Section 3.1. In addition, the present study provides insights into these developments and their potential relationships. The main question concerns whether a drop in real interest rates could potentially explain the macroeconomic developments presented in the following.

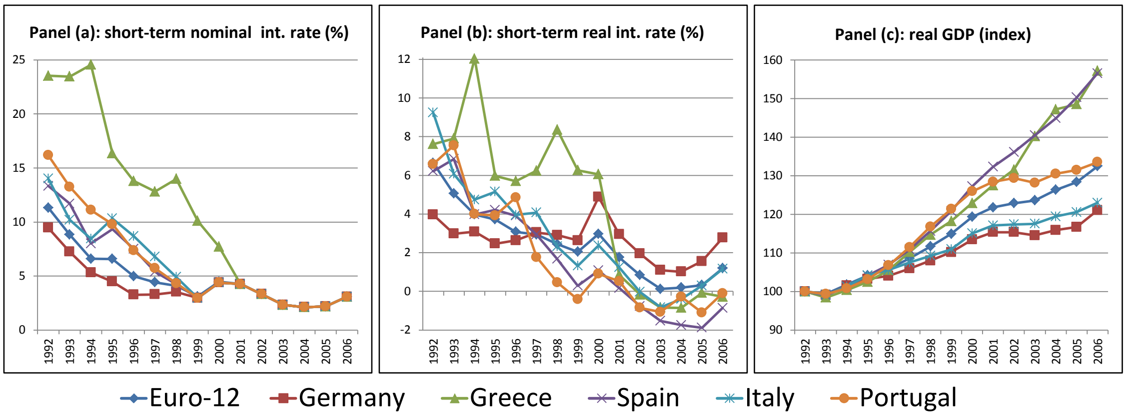

Fig. 3.1: Short-term nominal and real interest rates and the gross domestic product (GDP) (data source: AMECO).

First, the first Panel (a) in Figure 3.1 illustrates the (well-known) development of short-term nominal interest rates. From different levels, the nominal interest rates of all countries converged to a unit level after the eurozone was established. The main reasons for this convergence were the implementation of a common monetary policy and the disappearance of risk premia (e.g., see Fernández-Villaverde et al., 2013; Sinn, 2010, 2014). According to Panel (b) in Figure 3.1, the short-term real interest rates in the GIPS countries exhibited a declining trend over the whole 14-year period, with a tendency to level stabilization after the Euro was introduced. By contrast, the short-term real interest rate in Germany stagnated during the first seven-year period and then developed in parallel with the eurozone's average. By 1999 (but 2001 in Greece), the German short-term real interest rate was substantially higher than all of the other rates depicted. Finally, Panel (c) in Figure 3.1 shows how the real gross domestic product (GDP) grew over this time period, where the overall picture appeared to change around 2000. Before this date, Greece, Portugal, and Spain grew faster and Germany and Italy more slowly than the eurozone average. Subsequently, the growth rates slowed down in Portugal, Germany, and Italy, whereas Spain and Greece continued their rapid growth path.

Figure 3.2 illustrates developments in the labor market over time. Real wages increased in all countries except Spain, but they did not reach the growth levels in terms of the real GDP shown in Figure 3.1. If all else was equal, this should have caused a drop in the labor income share, which indeed was observed for all countries except Greece. However, the picture was more complicated due to substantial changes in total employment. In the eurozone, both real wages and employment increased, but because the real GDP grew faster, the labor income share decreased by nine percent over the whole time span. Germany's

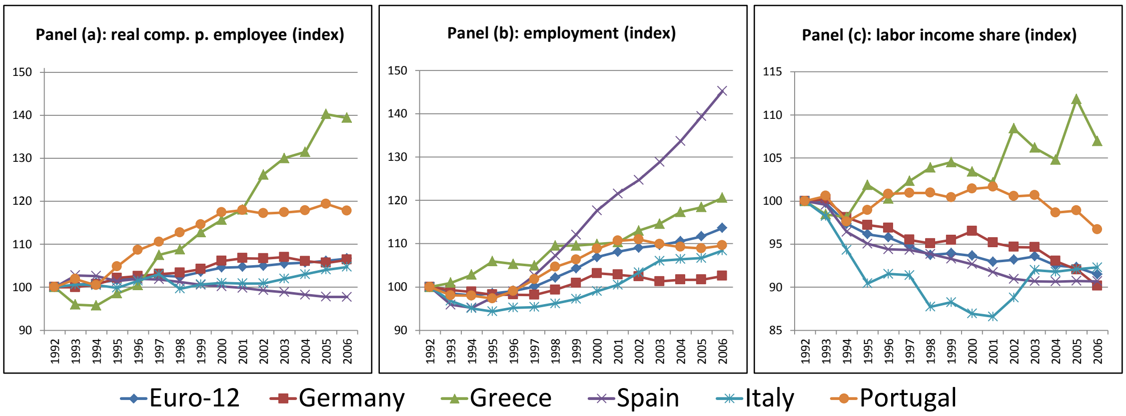

Fig. 3.2: Real compensation per employee, number of employees, and the labor income share (data source: AMECO and IMF).

real wages and its labor income share developed widely in line with the eurozone, but the similarity was explained by its relatively slow real GDP growth and widely stagnating employment. In addition, the Spanish labor income share closely followed the eurozone's average, but again the underlying factors differed, where skyrocketing real GDP growth was accompanied by a tremendous growth in employment of 45 percent and a slight decrease in real wages, thereby reducing the labor income share by a total of 9 percent. Italy's development is hardest to grasp; real wages stagnated over several periods, but they started to catch-up with the eurozone's average from 2002, while employment followed a "J-curve." Coupled with slow GDP growth, these variables transformed into a "U-shaped" labor income share, which decreased until 2001 and then increased subsequently. In Portugal, real wages and employment increased until the beginning of the new millennium and they stagnated subsequently. In addition to real GDP growth, these developments transformed into a labor income share that stagnated widely up to 2001 before then exhibiting a declining trend. In Greece, a tremendous growth in real wages coupled with a substantial growth in employment even outweighed the skyrocketing growth in real GDP; hence, the overall labor income increased as a share of GDP.

Figure 3.3 divides the GDP into its three main components, i.e., consumption in Panel (a), investment in Panel (b), and net exports in Panel (c). All of the values were calculated relative to the GDP. In the eurozone, these rates did not exhibit substantial trends over time. Germany's consumption rate remained stable, but the gross investment rate decreased and the net export rate increased after 2000. In Italy, there appeared to be a turning point around the years 1994 to 1996. Before this, the consumption and investment rates decreased, whereas the net export rate increased, but the trends reversed subsequently. Spain seems to have experienced a turning point around 1997, which was preceded by a decreasing consumption rate coupled with stable investment rate due to an increase in the net export rate. Subsequently, the consumption rate continued to decline, but a rapidly

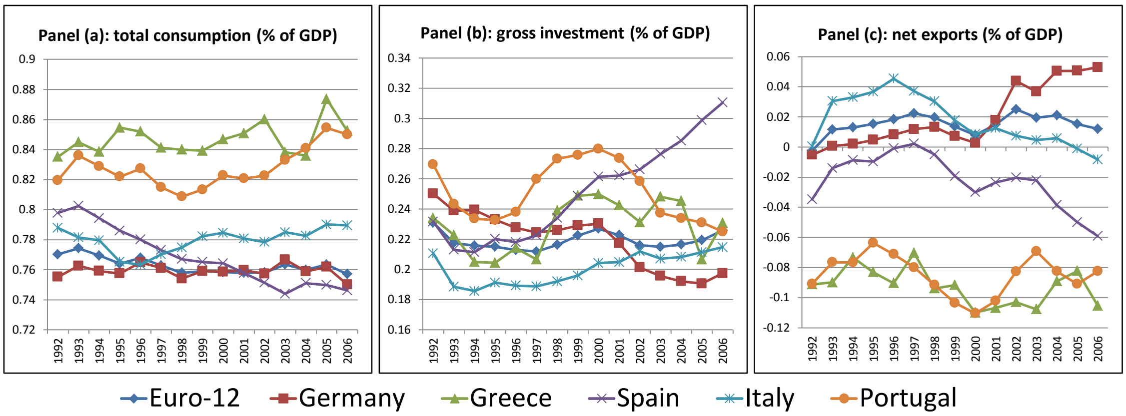

Fig. 3.3: Consumption, investment, and net exports as a share of GDP (data source: AMECO).

rising investment rate caused an increase in the net export rate. Portugal's comparably high consumption rate followed an increasing trend at least from 1999. Investment rates decreased until 1995, but then increased until a peak in 2000, before decreasing again subsequently. The opposite pattern applied to net exports, although it was less pronounced. Greece developed in a similar manner to Portugal, but with some differences in the first years of the new century.

Two main points should be mentioned. First, the developments in Greece, Italy, Portugal, and Spain differed widely. There were apparent similarities but they were often caused by very different factors, as shown by the labor income shares. In general, the differences in these variables may have been due to intrinsic causes (differences in country-specific parameters) or differences in country-specific development (e.g., the Olympic Games in Athens or the real estate bubble in Spain). Regardless of the cause, the generalizing label "GIPS" is not appropriate given the actual distinctive country-specific features. Second, the development of some countries exhibited a trend that broke around 1999, which can be treated as an indication of the shock effect due to the introduction of the Euro, as argued above.

A direct comparison between Portugal and Italy illustrates these heterogeneous country- and time-specific developments. Both countries experienced similar drops in nominal and real interest rates. In the run-up to the eurozone (between 1992 and 1999), strong Portuguese real GDP growth was accompanied by a great increase in real wages. By contrast, real GDP grew less in Italy, but real wages did not increase at all. Furthermore, these trends in wages were accompanied by an increase in the total number of employees in Portugal, whereas the total number of employees was below its 1992 level in Italy. After 1999, real wages and employment stagnated in Portugal, whereas they grew (slightly) in Italy. In summary, the Portuguese economy grew in the run-up to the Euro and stagnated subsequently, whereas the Italian economy stagnated until 1999 and subsequently caught up in terms of wages and employment.

Due to these heterogeneous time- and country-specific features, no stylized facts are proposed at this point, such as those made in previous studies (e.g., Fagan and Gaspar, 2007, 2008). Determining whether the following framework can explain the developments observed in the eurozone is considered in Section 3.2.5.

3.2.2 Micro-Foundation

The starting point of the theoretical examinations is a small open economy, the production side of which follows an aggregated CES production function (for a similar, although less mathematical setup, cp. Collignon, 2012, pp. 75–77). Technology A and a linear cost function are given. The CES technology generalizes the Cobb-Douglas function and allows a certain elasticity of substitution (σ) to be set exogenously. There are three agents in the economy: workers supplying labor in return for wage income, capitalists supplying capital in return for interest, and entrepreneurs who own firms and earn profit income. The economy produces one good at minimum costs using capital K and labor L, which are both supplied and demanded by perfectly competitive factor markets. Capital K is defined in a broad sense, by including both financial capital and real capital. α and β are the output elasticities of capital and labor. The total production costs are given by C. Both the production and the cost function are evaluated at the given price level P, so any inflationary pressure increases both output and costs. The formal representation of the economy is as follows.

$$\text{production function} \qquad Y(K,L) = P \cdot A \cdot (\alpha \cdot K^{-\frac{1-\sigma}{\sigma}} + \beta \cdot L^{-\frac{1-\sigma}{\sigma}})^{-\frac{\sigma}{1-\sigma}} \tag{3.1}$$

$$\text{cost function} \qquad C(K,L) = P \cdot (w \cdot L + r \cdot K) \tag{3.2}$$

$$\text{elasticities} \qquad \sigma, \alpha, \beta \in \,]0; \infty) \tag{3.3}$$

The model's micro-foundation is derived in three steps. First, conditional factor demand functions and the cost function, which all depend on r, w, and Y, are derived by cost minimization. Second, the output Y is transformed into an endogenous variable. Instead, L becomes exogenous. Third, wages w are endogenized and the profit income share x is used as an exogenous variable.

The optimization problem and the cost minimizing condition are as follows.

$$\text{optimization problem} \qquad min_{K,L} \;\; C(K,L) \;\; s.t. \;\; F(K,L) = \bar{Y} \tag{3.4}$$

$$\text{cost minimizing condition} \qquad -\frac{MP_K(K^*,L^*)}{MP_L(K^*,L^*} = TRS(K^*,L^*) = -\frac{r}{w} \tag{3.5}$$

By solving the optimization problem, we can derive the conditional factor demand functions $L(\cdot)$ and $K(\cdot)$, as well as the cost function $C(\cdot)$.

$$L(r,w,Y) = \frac{Y}{P \cdot A} \cdot (\frac{\beta}{w})^{\sigma} \cdot (\alpha^{\sigma} \cdot r^{1-\sigma} + \beta^{\sigma} \cdot w^{1-\sigma})^{\frac{\sigma}{1-\sigma}} \tag{3.6}$$

$$K(r,w,Y) = \frac{Y}{P \cdot A} \cdot (\frac{\alpha}{r})^{\sigma} \cdot (\alpha^{\sigma} \cdot r^{1-\sigma} + \beta^{\sigma} \cdot w^{1-\sigma})^{\frac{\sigma}{1-\sigma}} \tag{3.7}$$

$$C(r,w,Y) = \frac{Y}{A} \cdot (\alpha^{\sigma} \cdot r^{1-\sigma} + \beta^{\sigma} \cdot w^{1-\sigma})^{\frac{1}{1-\sigma}} \tag{3.8}$$

Thus, r, w, and Y are the exogenous variables in the system. In order to endogenize Y, the labor input L is assumed to be given. By solving both Equation 3.6 and 3.7 for Y and equating them, we can derive the new functions for capital demand $K(\cdot)$, and thus the new functions for production costs $C(\cdot)$ and output $Y(\cdot)$. All of the variables now depend on r, w, and L.

$$K(r,w,L) = L \cdot (\frac{\alpha}{\beta})^{\sigma} (\frac{w}{r})^{\sigma} \tag{3.9}$$

$$C(r,w,L) = P \cdot L \cdot (\frac{w}{\beta})^{\sigma} \cdot (\alpha^{\sigma} \cdot r^{1-\sigma} + \beta^{\sigma} \cdot w^{1-\sigma}) \tag{3.10}$$

$$Y(r,w,L) = P \cdot A \cdot L \cdot (\frac{w}{\beta})^{\sigma} \cdot (\alpha^{\sigma} \cdot r^{1-\sigma} + \beta^{\sigma} \cdot w^{1-\sigma})^{-\frac{\sigma}{1-\sigma}} \tag{3.11}$$

Collignon (2012) argued that policy makers in the eurozone stabilized profit margins. Hence, as a third step, profit income share x is set as a new exogenous variable and used to endogenize the variable wages w. The presence of profits is an exogenous assumption, which implicitly assumes that goods markets are characterized by a certain degree of imperfect competition, without explicitly modeling the goods markets equilibria. Profit income is given by the overall output Y minus overall production costs C. Profit income as a share of the total economy's output (Equation 3.12) is obtained by dividing the former expression by Y. Solving the resulting equation for w gives the wage function in Equation 3.13.

$$x = 1 - (\frac{1}{A}) \cdot (\alpha^{\sigma} \cdot r^{1-\sigma} + \beta^{\sigma} \cdot w^{1-\sigma})^{\frac{1}{1-\sigma}} \tag{3.12}$$

$$w(r,x) = \beta^{-\frac{\sigma}{1-\sigma}} \cdot [A^{1-\sigma} \cdot (1-x)^{1-\sigma} - \alpha^{\sigma} \cdot r^{1-\sigma}]^{\frac{1}{1-\sigma}} \tag{3.13}$$

Inserting Equation 3.13 into the former functions for capital K, costs C, and output Y (compare Equations 3.9, 3.10, and 3.11) yields the following expressions.

$$K(r,x,L) = L \cdot (\frac{\alpha}{r})^{\sigma} \cdot \beta^{-\frac{\sigma}{1-\sigma}} \cdot [A^{1-\sigma} \cdot (1-x)^{1-\sigma} - \alpha^{\sigma} \cdot r^{1-\sigma}]^{\frac{\sigma}{1-\sigma}} \tag{3.14}$$

$$Y(r,x,L) = P \cdot L \cdot A^{1-\sigma} \cdot \beta^{-\frac{\sigma}{1-\sigma}} \cdot [A^{1-\sigma} \cdot (1-x)^{1-\sigma} - \alpha^{\sigma} \cdot r^{1-\sigma}]^{\frac{\sigma}{1-\sigma}} \cdot (1-x)^{-\sigma} \tag{3.15}$$

$$C(r,x,L) = P \cdot L \cdot A^{1-\sigma} \cdot \beta^{-\frac{\sigma}{1-\sigma}} \cdot [A^{1-\sigma} \cdot (1-x)^{1-\sigma} - \alpha^{\sigma} \cdot r^{1-\sigma}]^{\frac{\sigma}{1-\sigma}} \cdot (1-x)^{1-\sigma} \tag{3.16}$$

Now, we can derive the labor income $LI(\cdot)$, capital income $CI(\cdot)$, and profit income $PI(\cdot)$, as well as the labor income share $LIS(\cdot)$, the capital income share $KIS(\cdot)$, and the profit income share $PIS(\cdot)$.

$$LI(r,x,L) = P \cdot L \cdot \beta^{-\frac{\sigma}{1-\sigma}} \cdot [A^{1-\sigma} \cdot (1-x)^{1-\sigma} - \alpha^{\sigma} \cdot r^{1-\sigma}]^{\frac{1}{1-\sigma}} \tag{3.17}$$

$$KI(r,x,L) = P \cdot L \cdot \beta^{-\frac{\sigma}{1-\sigma}} \cdot \alpha^{\sigma} \cdot r^{1-\sigma} \cdot [A^{1-\sigma} \cdot (1-x)^{1-\sigma} - \alpha^{\sigma} \cdot r^{1-\sigma}]^{\frac{\sigma}{1-\sigma}} \tag{3.18}$$

$$PI(r,x,L) = x \cdot Y(r,x,L) \tag{3.19}$$

$$LIS(r,x) = A^{\sigma-1} \cdot [A^{1-\sigma} \cdot (1-x)^{1-\sigma} - \alpha^{\sigma} \cdot r^{1-\sigma}] \cdot (1-x)^{\sigma} \tag{3.20}$$

$$KIS(r,x) = A^{\sigma-1} \cdot \alpha^{\sigma} \cdot r^{1-\sigma} \cdot (1-x)^{\sigma} \tag{3.21}$$

$$PIS(x) = x \tag{3.22}$$

3.2.3 Macro-Integration

Two national account identities have been used, i.e., the output by production accounts, which is set by the CES production function, and the output by income accounts, which is defined as the sum of the profit, capital, and labor income. The remaining identity, i.e., the output by expenditure accounts, is then added to complete the system. The following summarizes all three national income identities, which are again assessed at the price level P.

$$Y(r,x,L) = P \cdot A \cdot (\alpha \cdot K(r,x,L)^{-\frac{1-\sigma}{\sigma}} + \beta \cdot L^{-\frac{1-\sigma}{\sigma}})^{-\frac{\sigma}{1-\sigma}} \tag{3.23}$$

$$Y(r,x,L) = P \cdot [LI(r,x,L) + KI(r,x,L) + PI(r,x,L)] \tag{3.24}$$

$$Y(r,x,L) = P \cdot [Cons(r,x,L) + Inv(r,x,L) + NX(r,x,L)] \tag{3.25}$$

$NX(\cdot)$ is the amount of net exports, which is defined as the current account side of the balance of payments. By definition, the current account equals the capital account, which equals the negative amount of capital borrowed from abroad (i.e., B_{abr}).

$$NX(r,x,L) = -B_{abr}(r,x,L) \tag{3.26}$$

Moreover, the amount of domestic investment $Inv(\cdot)$ is financed by the amount of domestic savings plus the amount of capital borrowed from abroad.

$$Inv(r, x, L) = S_d(r, x, L) + B_{abr}(r, x, L) \tag{3.27}$$

Investment $Inv(\cdot)$ follows a general investment function, where $i(\cdot)$ is the overall domestic investment rate for given values of p and q.

$$Inv(r, x, L) = Y(r, x, L) \cdot i(r) \tag{3.28}$$

$$i(r) = p - q \cdot r \tag{3.29}$$

Domestic savings $S_d(\cdot)$ are given by the savings share on labor, capital, and profit income. The corresponding saving rates for workers, capitalists, and entrepreneurs are given by s_L, s_K, and s_Π. The overall domestic saving rate $s(\cdot)$ and the analogous overall domestic consumption rate $c(\cdot)$ are derived as follows.

$$s(r, x) = s_L \cdot LIS(x) + s_K \cdot KIS(r, x) + s_\Pi \cdot PIS(x) \tag{3.30}$$

$$c(r, x) = (1 - s_L) \cdot LIS(x) + (1 - s_K) \cdot KIS(r, x) + (1 - s_\Pi) \cdot PIS(x) \tag{3.31}$$

Finally, according to the saving-investment condition in Equation 3.27, the domestic rate of borrowing from abroad $b_{abr}(\cdot)$ is derived by subtracting the overall domestic saving rate $s(\cdot)$ from the overall domestic investment rate $i(\cdot)$.

$$b_{abr}(r, x) = i(r) - s(r, x) \tag{3.32}$$

Using the results from Section 3.2.2, the rates for savings, consumption, and borrowing from abroad can be reformulated as the following expressions.

$$s(r, x) = s_L + (s_\Pi - s_L) \cdot x + (s_K - s_L) \cdot A^{\sigma-1} \cdot \alpha^\sigma \cdot r^{1-\sigma} \cdot (1 - x)^\sigma \tag{3.33}$$

$$c(r, x) = 1 - s_L - (s_\Pi - s_L) \cdot x - (s_K - s_L) \cdot A^{\sigma-1} \cdot \alpha^\sigma \cdot r^{1-\sigma} \cdot (1 - x)^\sigma \tag{3.34}$$

$$b_{abr}(r, x) = p - q \cdot r - s_L - (s_\Pi - s_L) \cdot x - (s_K - s_L) \cdot A^{\sigma-1} \cdot \alpha^\sigma \cdot r^{1-\sigma} \cdot (1 - x)^\sigma \tag{3.35}$$

3.2.4 Comparative Statics

In order to assess how a shock in the real interest rate affects the economy, we derive the first derivatives of the variables of interests (i.e., real output, real wages, and the respective rates for consumption, savings, investment, and borrowing from abroad).

$$\frac{\partial Y(r,x,L)}{\partial r} = -(\frac{\alpha}{r})^{\sigma} \cdot \sigma \cdot P \cdot L \cdot A^{1-\sigma} \cdot \beta^{-\frac{\sigma}{1-\sigma}} \cdot Z^{\frac{2\sigma-1}{1-\sigma}} \cdot (1-x)^{-\sigma} \tag{3.36}$$

$$\frac{\partial w(r,x)}{\partial r} = -(\frac{\alpha}{r})^{\sigma} \cdot \beta^{-\frac{\sigma}{1-\sigma}} \cdot Z^{\frac{\sigma}{1-\sigma}} \tag{3.37}$$

$$\frac{\partial LIS(r,x)}{\partial r} = -(\frac{\alpha}{r})^{\sigma} \cdot A^{\sigma-1} \cdot (1-x)^{\sigma} \cdot (1-\sigma) \tag{3.38}$$

$$\frac{\partial s(r,x)}{\partial r} = (1-\sigma) \cdot (s_K - s_L) \cdot (1-x)^{\sigma} \cdot A^{\sigma-1} \cdot (\frac{\alpha}{r})^{\sigma} \tag{3.39}$$

$$\frac{\partial c(r,x)}{\partial r} = -(1-\sigma) \cdot (s_K - s_L) \cdot (1-x)^{\sigma} \cdot A^{\sigma-1} \cdot (\frac{\alpha}{r})^{\sigma} \tag{3.40}$$

$$\frac{\partial i(r)}{\partial r} = -q \tag{3.41}$$

$$\frac{\partial b_{abr}(r,x)}{\partial r} = -q - (1-\sigma) \cdot (s_K - s_L) \cdot (1-x)^{\sigma} \cdot A^{\sigma-1} \cdot (\frac{\alpha}{r})^{\sigma} \tag{3.42}$$

$Z = A^{1-\sigma} \cdot (1-x)^{1-\sigma} - \alpha^{\sigma} \cdot r^{1-\sigma}$ depends on the initially given parameter A, α, σ, x, and r, which must be positive in order to guarantee a positive output Y (compare Equation 3.15). Equations 3.36 and 3.37 show that a negative interest rate shock (a drop in real interest rates) unconditionally increases the real output $Y(\cdot)$ and real wages $w(\cdot)$. Real wages grow stronger than real output if the labor income share $LIS(\cdot)$ grows, which holds provided that the elasticity of substitution σ is smaller than unity (compare Equation 3.38). If this elasticity is given and the saving rates for workers s_L is smaller than the rate of capital owners s_K, then a negative interest rate shock decreases the overall saving rate $s(\cdot)$ and increases the overall consumption rate $c(\cdot)$ (compare Equations 3.39 and 3.40). Moreover, under these assumptions, a negative real interest rate shock increases both overall investment $i(\cdot)$ and borrowing from abroad $b_{abr}(\cdot)$.

3.2.5 Discussion

In this study, we investigated the nature of macroeconomic imbalances by integrating a microeconomic framework into a national income accounting system. The power of this procedure is attributable to its macroeconomic consistency and its analytical solvability. Moreover, by keeping the consumption behavior constant, it is possible to extract adjustments that occur purely through the logic of “balances mechanics.” Nonetheless, if a certain behavioral assumption is of interest, the equations derived in Sections 3.2.2 and 3.2.2 can also be differentiated with respect to behavioral variables such as the individual saving rates s_L, s_K, s_{Π}, thereby determining the respective adjustments following behavioral changes.

In this study, we modeled the effect of an initial real interest rate shock, so the exogeneity of r is a methodological necessity. From a real-world perspective, the risk-adjusted real interest rate for a small open economy with its own currency will depend greatly on the average real interest rate, which is prevalent in the economy's supranational financial framework (e.g., the European Exchange Mechanism, ERM I, before 1999). According to the critique by Walters (1986), this logic changes in a monetary union, where due to a common exogenous nominal interest rate, a country's risk-adjusted real interest rate will depend negatively on the country's inflation rate. The price level P, which would be affected according to the Walters critique, only affects the overall output and costs (cp. Equations 3.15 and 3.16), so the framework proposed in the present study does not consider this relationship for reasons of simplicity.

In Section 3.2.2, the output Y was endogenized and replaced by the labor input L as an exogenous variable in order to assess the effect of a real interest rate shock on the real output, which appears to be more influential than employment effects in the context of this study. Moreover, the comparative statics analysis showed that the labor input has only a weighting effect on output changes, whereas the other variables of interest do not depend on L (compare Equations 3.36 to 3.42). However, the opposite effects on labor input can be derived for a given real output if necessary by solving Equation 3.15 for L.

The third exogenous variable is the profit income share x. This was motivated by the discussion given by Collignon (2012), who argued that policy makers in the eurozone stabilized profit margins. As mentioned earlier, it is assumed that profits are exogenous and not based on any specific features of the goods markets. Nevertheless, this can be justified if we claim that international competition lowers the profits of firms, but that a certain profit margin can always be realized for several reasons (such as the distinct and unique characteristics of a single firm's product). The presence of profits is also reasonable if they are viewed as the disbursement of the entrepreneurs. Given these considerations, the exogenous use of profit margins is a non-problematic step. Furthermore, it allows the endogenization of wages w, which is of great interest in the current context.

In addition to these variables, the price level P and technological level A are also exogenous. It is implicitly assumed that globalization leads to an internationally developed and spread technological level, without any substantial influence from a single small open economy. Price changes are viewed as a monetary phenomenon, which affect both production and the cost function simultaneously. In the initial setup selected for a cost minimizing economy, both variables only had a weighting function, which does not change throughout the framework derived subsequently. For example, in Equations 3.39 to 3.42, technology A had equal effects on all derivatives and the price level P was already cancelled out.

Furthermore, the approach employed made some simplifying assumptions, i.e., the economy produces only one good, synonymously denoting a representative goods bundle, using only two factors for production, and no differentiation between a public and a governmental sector. Moreover, the return on all capital invested remains in the country and belongs completely to the country's total income. Further studies may relax these assumptions, but this approach was not considered in this study due to reasons of simplicity and analytical resolvability.

The results obtained demonstrate the crucial importance of two variables: the elasticity of substitution between labor and capital, and the savings rate for workers. If the elasticity σ is low (i.e., between zero and one), capital is an imperfect substitute for labor. Thus, workers and unions are in a position to conduct more extensive wage bargaining, so the real wage increases faster than the real output. As a consequence, a negative interest rate shock increases the labor income share $LIS(\cdot)$ in Equation 3.38 only if the elasticity substitution σ is less than one. Previous empirical studies employed a substitution elasticity between 0.1 and 0.8, but most often close to 0.5 (for an overview of relevant literature, see Cantore et al., 2014). These empirical findings and their fundamental theoretical relevance (as exemplified above) should be stressed because most theoretical studies rely on a Cobb-Douglas specification with $\sigma = 1$. In terms of individual saving rates, workers are likely to have a lower savings rate than capitalists if we assume that capitalists have a higher income than workers and that the marginal propensity to consume decreases with income. The latter assumption can be traced back to John Maynard Keynes (Keynes, 1936, p. 96), who in his General Theory stated '[...] that men are disposed, as a rule and on the average, to increase their consumption as their income increases, but not by as much as the increase in their income.' More recently, Helmedag (2008) illustrated the importance of different saving rates for explaining demand effects on income distribution. The results of the present study support this evaluation.

3.2.6 Empirical Relevance

In the following, it is assumed that σ is smaller than unity and that workers have a lower savings rate compared with capitalists ($s_L < s_K$). According to Equations 3.36 to 3.42, a ceteris paribus drop in the real interest rate r increases real wages w, the labor income share LIS, and the rates of consumption c, investment i, and borrowing from abroad b_{abr}.

This matches exactly with the directions of the changes seen in the Greek data in the run up to the Euro from 1992 and 2001 (compare Figures 3.1 to 3.3).[1] Shortening the run-up period to seven years (from 1994 to 2001) in order to ensure better comparability with other GIPS countries does not change this finding. Moreover, the match also holds for the whole period between 1992 and 2006, and for the five years after the Euro's introduction, except for a drop in the investment rate and a stagnating consumption rate after 2001.

In Portugal, macroeconomic developments in the run up to the Euro (1992 to 1999) were similar to the theoretical implications, except for a slight decrease in the consumption rate and a stagnating labor income share. The developments between 1999 and 2006 did not fit to the theoretical model.

The data for Italy between 1992 and 1999 did not agree with the theoretical implications, where they were almost exactly the opposite, i.e., wages stagnated, the share of labor income and the rates of consumption and investment decreased, and the net export rate increased. However, between 1999 and 2006, the trends in the Italian data matched the model's outcomes exactly. This suggests country-specific time heterogeneity, as mentioned in Section 3.2.1, where the real interest rate shock might have had a delayed effect in Italy compared with Greece.

The implications of the theoretical model were rejected by the Spanish data. In the first seven-year period, the labor income share, rate of consumption, and net export rate moved in the opposite direction. In the second seven-year period, the opposite trends were observed for real wages, the labor income share, and the consumption rate. Apparently, substantially different factors and discrete behavioral changes occurred in Spain. The real estate bubble accompanied by a substantial drop in consumption and a tremendous increase in investments probably comprised the main explanations for the events in Spain.

3.3 Concluding Remarks

In this study, we investigated the macroeconomic effects of a real interest rate decrease on a small open economy. The underlying question is whether a drop in real interest rates in the run-up to the eurozone and during its first decade could explain the range of macroeconomic changes in the GIPS countries, including adjustments in real wages and the labor income share, as well as rates of consumption, investment, and net exports.

[1] The model variable b_{abr} corresponds to the negative value of the "net export rate" variable in Section 3.2.1, which follows from the balance of payments in the sense that the current and the capital account must match each other.

First, we discussed the real world macroeconomic developments observed in the eurozone between 1992 and 2006. Next, we derived the model's micro-foundation, i.e., a cost-minimizing CES economy, which we subsequently integrated into a macroeconomic framework of income accounting identities. In this context, the real interest rate r, labor income L, and profit income share x were used as exogenous variables, thereby allowing the endogenization of wages w and output Y. Comparative statics were then derived and the model's implications are discussed. The crucial roles of the elasticity of substitution and agent-specific saving rates were demonstrated. Finally, the theoretical comparative statics were compared with the previously discussed empirical data.

The proposed model conforms to the idea that macroeconomic developments can be explained partly by "balances mechanics" (as proposed by Stützel in 1958), thereby abstracting from any (inter-temporal) behavioral change with respect to consumption. The latter is the main deviation from previous theoretical studies, which typically modeled behavioral adjustments with respect to an inter-temporal budget constraint. However, the justification for these approaches varies due to the assumption of rational economic agents. The Euro crisis and subsequent developments have shown clearly that inter-temporal rational consumption behavior was widely not in place in the eurozone, at least not at the macroeconomic level. However, to simply assume the opposite, i.e., irrational and irresponsible behavior, does not appear to be useful, but instead it is speculative and normative. Hence, the present study focused on the "mechanical" adjustments in income accounting identities, which were caused by an exogenous drop in real interest rates.

The present study showed that for some countries and time periods (including Greece in the run up to the eurozone and Italy after the introduction of the Euro), the signs of all the macroeconomic trends considered could be derived theoretically using the model. This indicates that the appearance of imbalances does not have to be caused (purely) by behavioral changes, but instead they might be a partial consequence of a shock to a static economic system. It should be noted that the implications of the model did not agree with the Spanish data, probably because strong behavioral changes occurred throughout the time period considered, where the tremendous real estate boom substantially affected the trends in most of the macroeconomic variables. In general, and irrespective of the theoretical or empirical approach, future research should carefully consider the distinct heterogeneity across GIPS countries, as illustrated in Section 3.2.1.

In addition to the empirical relevance of this study, two theoretical results should be stressed. First, the size of the elasticity of substitution is of crucial importance for the outcome of the model. To make the model agree with empirical observations in the eurozone, the elasticity of substitution had to be set at less than unity. Previous empirical investigations also proposed using an elasticity of substitution less than unity (Cantore et al., 2014), so theoretical researchers should reconsider the dominant position of Cobb-Douglas specifications in economic modeling. A second pivotal result is related to saving rates. Similar to the elasticity of substitution, the model could only match the empirical observations when we assumed that the savings rate for employees was below that for capital owners. John Maynard Keynes (Keynes, 1936, p. 96) called this assumption a "fundamental psychological law," which clearly expresses his firm belief in this principle. Although it was self-evident to Keynes, this assumption has made little impact on textbook economics. Thus, a consideration of different saving rates appears to be necessary in future economic models.

In addition to these two general remarks, further research might also extend the proposed framework by differentiating between traded and non-traded goods, and by incorporating human capital and a governmental sector. Moreover, given the stagnation of real GDP growth since 1999 in many eurozone countries, the effects on growth of the introduction of the Euro continue to require thorough theoretical and empirical investigations.

Chapter 4

Club Convergence and Clustering Algorithms

Monte Carlo experiments were used to assess the performance of Phillips and Sul's (2007, 2009) clustering methodology. Cluster outcomes improve considerably if the Phillips and Sul (2007) algorithm is extended by a club merging algorithm. For more heterogeneous panels, a hierarchical clustering algorithm is proposed that performs better than the extended Phillips and Sul methodology.

JEL classification: C23, C38, C50, C52

Keywords: club convergence, common factor, log t regression test, relative convergence, panel data, transition

Subtitle: Monte Carlo Insights to the Non-Linear Single Factor Model

4.1 Introduction

Phillips and Sul (2007) (PS) proposed an innovative factor model for panel data, which represents economies in transition by considering individual time varying heterogeneity. The factor model splits the variable of interest into a common factor and a time-varying idiosyncratic factor loading. Based on this model, PS also developed the log t test (a simple test for convergence), a clustering algorithm to identify convergence clubs, and a club merging rule (PS, 2009). The PS methodology is able to detect convergence clubs in panel data, even if panel units pass through phases of transition, where evidence for club convergence is blurred or hidden.

Given that the club convergence hypothesis (Azariadis and Drazen, 1990; Azariadis, 1996; Galor, 1996) has gained increased interest in academia, it is not surprising that the PS approach has become a workhorse procedure in the empirical literature. It has been applied to test for convergence in CO_2-emissions (Camarero et al., 2013), health care expenditures (Panopoulou and Pantelidis, 2013), bank efficiency (Matousek et al., 2015), US house prices (Montañés and Olmos, 2013), corporate tax rates (Regis et al., 2015), and regional income per capita (Bartkowska and Riedl, 2012).

Aside from Lyncker and Thoennessen (2017), who proposed two post clustering algorithms to finalize club formation, and a Monte Carlo experiment conducted by Fritsche and Kuzin (2011), no methodological contribution to the PS procedure has been achieved. Nonetheless, the PS (2007) clustering algorithm incorporates features that are worth critical appraisal. In Step 1, the initial ordering according to the last panel observations is likely to predetermine the subsequent clustering procedure. In Step 2, rejection of the log t test for the first two elements discards the first element from the core group formation, ignoring the possibility that the second element is the one that does not belong to the local core group. In Step 3, the initial choice of the critical value and its adjustment are discrete decisions, and so the resulting regression quality could suffer in cases where convergence clubs are detected using different critical values.

Based on this critical appraisal, this study targets two questions: first, whether the PS (2007) algorithm combined with a club merging algorithm similar to the one proposed by (Lyncker and Thoennessen, 2017) leads to a more precise clustering than the standard PS (2007, 2009) methodology; second, whether the HC algorithm leads to a more precise clustering than the extended PS (EPS) procedure, i.e., the PS algorithm combined with the club merging algorithm. Both objectives were evaluated using Monte Carlo experiments. The first set of simulations determined the optimal critical value c (see Step 3 of the PS algorithm) in the EPS procedure, which allowed evaluation of whether the EPS procedure at the recommended critical value, c, perform better than the standard PS (2007,2009) methodology. The second set of simulations compared the EPS procedure with the HC algorithm. Throughout the study, five different quality measures were used to assess the respective clustering precision of the investigated methods.

Very high critical values (e.g. $c = 100$) considerably improved EPS performance, and at the recommended critical value, EPS outperformed standard PS (2007,2009) methodology. The HC algorithm was better than EPS for narrow panels (N=20 & T=10,30,50), but poorer for short and broader panels (T=10 & N=50,100). Different Monte Carlo specifications show that the HC algorithm is more appropriate than EPS for heterogeneous panels, whereas EPS is superior if the panel variance is high and if clubs growth paths develop close to each other.

Section 4.2 presents two (post-)clustering algorithms and the Monte Carlo simulation setup and strategy. Results and underlying dynamics are discussed in Section 4.3, and concluding remarks are provided in Section 4.4.

4.2 Simulation Strategy

4.2.1 Extended Phillips Sul Procedure

The EPS procedure comprises two procedures, i.e. the standard PS clustering algorithm (Phillips and Sul, 2007) and a club merging algorithm. This study employs the following club merging algorithm as the second element of the EPS.

1. For a given number of clubs P, conduct pairwise log t tests of all adjacent clubs. Store the corresponding convergence test statistics $t_{\hat{b}}$.
2. Choose the largest $t_{\hat{b}}$. If $t_{\hat{b}}$ exceeds the tabulated t at the chosen level of significance (e.g. -1.645 at the 5% level), clubs are merged to constitute a new convergence club. If not, the algorithm stops.
3. If at least two clubs are left, the algorithm starts again at Step 1. If not, the algorithm stops.

A very similar club merging algorithm, which formalized the club merging rule given in Phillips and Sul (2009), was proposed by Lyncker and Thoennessen (2017). The difference between both club merging algorithms is that the one proposed here does not consider the ordering of elements in the club merging vector (calculated in Step 1), but simply chooses the highest element.Thus, the algorithm proposed and used here follows a more general merging rule.

Evaluation of the question whether EPS improves the standard PS (2007,2009) approch raises the problem that the club merging rule outlined in PS (2009) is based on a discrete assessment whether adjacent clubs should be merged. PS (2009) did not outline any rule for border cases, which ultimately motivated Lyncker and Thoennessen (2017) to propose a club merging algorithm. Monte Carlo simulations, however, require precise inputs; a discrete adjacent club merging rule is not sufficient. Hence, the EPS outcomes at $c = 0$ were taken as proxies for the standard PS (2007,2009) outcomes. This seems appropriate, since the club merging algorithm proposed here is only a formalization of the club merging rule (PS 2009), and for the critical value, $c = 0$, cluster outcomes of both methods will be very similar or equal in nearly all cases.

4.2.2 Hierarchical Clustering Algorithm

For many panels, the issues raised in the critical appraisal of the PS (2007) clustering algorithm (cp. Section 4.1) are either advantageous or irrelevant. However, a more general clustering algorithm might be more appropriate for some panels. This paper proposes a hierarchical clustering (HC) algorithm as an alternative to the PS (2007, 2009) clustering procedure.

1. For a panel of size N, run all possible pairwise log t tests of unit i and unit j for $i, j = 1, 2, \cdots, N$ and $i \neq j$. Collect all t_{ij}.

2. Choose the largest t_{ij}. If t_{ij} exceeds the tabulated t at the chosen level of significance (e.g. -1.645 at the 5% level), units i and j are merged to a convergence club. If not, all remaining units of the panel are either diverging units or convergence clubs, and the algorithm stops.

3. Treat the newly clustered convergence club as a single unit of the whole panel, such that the current panel size decreases by 1. Repeat Steps 1 to 3 until the algorithm terminates.

In the first step, the log t test is used as an objective function to construct a type of similarity matrix. The highest calculated t-value is the criterion to either merge the respective elements or stop clustering. Since the log t test employs sigma variance, the HC algorithm clusters in the tradition of Ward (1963) according to the smallest increase of the within club variance.

The proposed procedure is the most general way to cluster elements using the log t test. Neither last observation ordering nor discrete choice of any critical value is required, avoiding any predetermination in the clustering procedure. Also, no post clustering merging procedure or algorithm is required for cluster finalization.

4.2.3 Data Generation

The data generating process (DGP) strictly follows that in Section 5 of PS (2007). The created panel, X_{it}, of length T $(t = 1, ..., T)$ and width N $(i = 1, ..., N)$ reproduces the non-linear single factor model as proposed by PS (2007). Hence,

$$X_{it} = \delta_{it}\mu_t, \tag{4.1}$$

where $\delta_{it} = \delta_i + \delta_{it}^0$ and $\delta_{it}^0 = \rho_i\delta_{it-1}^0 + \epsilon_{it}$. If $\rho_i \sim U[0, \rho]$ for $\rho < 1$, and $\epsilon_{it} \sim \; iidN(0, \sigma_i^2 L(t+1)^{-2}t^{-2\alpha})$ with $L(t+1) = \log(t+1)$, a slowly varying and converging evolution of the transition parameter, δ_{it}, is ensured. Setting $\sigma_i \sim \; U[0.02, 0.28]$ guarantees at the 97.5% lower confidence limit that $\delta_{it} > 0$ at $t = 1$. For any $\delta_{it} < 0$, the whole pathway of unit i is dropped and re-simulated. No specification is required for μ_t, since it cancels in the application of the log t test. The unit specific growth path, δ_i;convergence speed, α; and ρ are discretely set for each simulation.

4.2.4 Simulation Setup

As outlined above, the Monte Carlo study has two focuses: first, to investigate whether EPS produces better results than standard PS (2007,2009); second, to compare EPS with the HC algorithm. Monte Carlo experiments to target each of these two questions comprise six different specifications and 36 simulations per specification, a total number of 432 simulations à 2000 replications, as summarized in Table 4.1.

MC 1 is the baseline simulation, and tests EPS and HC on panels of length T $(T = 10, 30, 50)$ and width N $(N = 20, 50, 100)$. Panel units converge at speed α (with $\alpha = 0.01, 0.05, 0.1, 0.2)$ to the respective growth path (with $\delta_1 = 1.0$ and $\delta_2 = 1.2$) of two same-sized clubs. MC 2 to MC 6 deviate from the DGP of the baseline scenario with respect to the distance between clubs, number of clubs, presence of diverging regions, and persistence of transitional heterogeneity.

4.2.5 Result Evaluation

Simulations were evaluated for five different criteria: *size* measured the rate the respective procedure fails to assign elements to the correct club, *power* measured the rate non-club elements are correctly excluded from the respective club. These two criteria – also used

Table 4.1: Setup of Monte Carlo simulations.

	MC 1	MC 2	MC 3	MC 4	MC 5	MC 6
T	10;30;50	10;30;50	10;30;50	10;30;50	10;30;50	10;30;50
N	20;50;100	20;50;100	20;50;100	20;50;100	20;50;100	20;50;100
# clubs	2	2	2	**5**	2	2
# div. regions	-	-	-	-	**2**	-
δ_1	1.0	1.0	1.0	1.0	1.0	1.0
δ_2	1.2	**1.1**	**1.3**	1.2	1.2	1.2
δ_3	-	-	-	**1.4**	-	-
δ_4	-	-	-	**1.6**	-	-
δ_5	-	-	-	**1.8**	-	-
δ_{div1}	-	-	-	-	**1.1**	-
δ_{div2}	-	-	-	-	**1.3**	-
ρ	0.5	0.5	0.5	0.5	0.5	**0.9**
α	0.01;0.05; 0.1;0.2	0.01;0.05; 0.1;0.2	0.01;0.05; 0.1;0.2	0.01;0.05; 0.1;0.2	0.01;0.05; 0.1;0.2	0.01;0.05; 0.1;0.2
$t - value$	-1.645	-1.645	-1.645	-1.645	-1.645	-1.645
# replications	2000	2000	2000	2000	2000	2000
# simul. EPS	36	36	36	36	36	36
# simul. HC	36	36	36	36	36	36

Notes: Clubs are always of the same size. The EPS procedure was performed for critical values $c = -1.645, -1, 0, 1, 5, 10, 50, 100$. All simulations were conducted using Matlab R2013a and R2015a. Codes are available on request.

in the Monte Carlo section presented in PS (2007) – measure the precision of clustering: lower *size* or higher *power* mean improved clustering quality. Ultimately, they depend on the probabilities of committing type I and type II errors in the log t tests across the clustering procedure. Note however that this study checks the properties of different clustering methods and not the properties of the log t test itself.

For all simulations except MC 4 and MC 5, $size + power = 1$, since the underlying DGP models two same-sized clubs. Any minor deviations from this are the result of incorrectly detected diverging regions, which – all else being equal – either increase *size* or *power*. In addition, the criterion *detection* was also calculated, which measured the probability that an algorithm detects the correct number of clubs. *detection* is a newly proposed criterion that has not been employed previously.

To assess the overall quality of clustering under the three criteria, two measures are proposed: $sum = (1 - size + power + detection)/3$; $grade = (power - size) * detection$. These novel quality criteria incorporate the occasional trade-off between *detection* against *size* and *power*, and hence provide an appropriate comparison of different specifications. All five measures are defined in the interval $[0, 1]$. Table 4.2 summarizes the criteria and the notation of recommendations used in Section 4.3.

Note that *size* and *power* can only be calculated if the algorithm has identified the correct number of clubs. For example, if the correct number of clubs is two, but the applied

Table 4.2: Performance criteria of algorithms and notation of recommendations.

criteria		defined in
size	probability of failing a correct club assignments of units	$[0, 1]$
power	probability of achieving a correct club exclusion of units	$[0, 1]$
detection	probability to detect the correct number of clubs	$[0, 1]$
sum	$(1 - size + power + detection)/3$	$[0, 1]$
grade	$(power - size) * detection$	$[0, 1]$
notation		
c	critical value set in Step 3 of the PS algorithm	
c^{EPS}	EPS procedure with respective c recommended	
c^{HC}	HC algorithm recommended	
c^{**}	no substantial performance advantage of one procedure (difference less than 0.01)	

Notes: Theoretical cases, where *size* > *power* and hence *grade* is defined in $[-1, 1]$, are not relevant in this study.

procedure detects three clubs, the calculation of *size* and *power* would require assigning the three detected clubs to the two existing clubs. Since such an assignment would be ambiguous, or impossible in many cases, it is not possible to measure the quality of correctly assigning and excluding units from clubs. However, there is no reason *size* and *power* should be different in cases where the underlying procedure does not identify the correct number of clubs. Hence, the calculated values of *size* and *power* are assessed as generally representative for the respective panel and the respective clustering procedure.

4.3 Results

4.3.1 Critical Value for Extended Phillips Sul Procedure

The results presented are based on a simple average across all six Monte Carlo specifications and all four convergence speeds. Detailed results of each Monte Carlo for different convergence speeds are provided in the Appendix. Throughout this and the following sections, the term 'improvement' is used to measure the absolute improvement in clustering precision, measured by the five criteria *size*, *power*, *detection*, *sum*, and *grade*. For example, if the calculated *sizes* of method A and method B are 0.15 and 0.10, the absolute size improvement from B against A is 0.05.

Figure 4.1 shows EPS performance for critical value $c = -1.645$ to $c = -1, 0, 1, 5, 10, 50, 100$, averaged across all T and N. There is strong improvement of all five criteria up to $c = 5$ and moderate improvement subsequently. *size* and *power* improve by approximately 7—9 percentage points, and *detection* by approximately 4 percentage points. The *sum* and *grade* curves confirm these improvements.

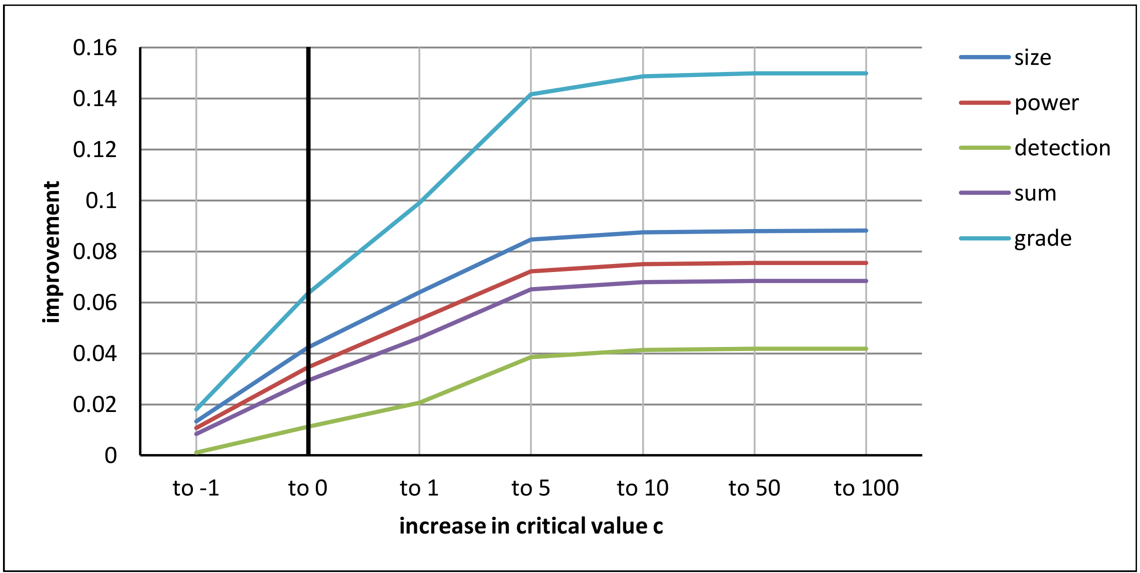

Fig. 4.1: All MCs: extended Phillips and Sul (EPS) performance with differing critical value. The improvement of the variable *size* measures the absolute decrease in *size*.

Figure 4.4 shows the curves are similar for all MC specifications, with different improvement rates. Consider MC 1 as the reference specification. Then performance improvement is stronger if the club specific growth paths, δ_i, evolve more closely to each other (MC 2) and if unit specific transitional heterogeneity is stronger (higher ρ in MC 6). In contrast, the inclusion of diverging units in the DGP (MC 5) decreases performance improvement. If the panel contains five clubs rather than two (MC 4), all criteria except *size* exhibit a less pronounced improvement.

Table 4.3: All MCs: recommended critical values c and recommended algorithm (average across αs).

T	N	size	power	detection	sum	grade
10	20	100^{HC}	100**	10**	10^{HC}	10**
10	50	50**	50**	100^{EPS}	50^{EPS}	100^{EPS}
10	100	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
30	20	100**	100**	1^{HC}	1^{HC}	1^{HC}
30	50	100^{EPS}	100^{EPS}	100^{HC}	100**	100**
30	100	100^{EPS}	100^{EPS}	100^{HC}	100^{EPS}	100^{EPS}
50	20	1**	100**	-1^{HC}	1^{HC}	1^{HC}
50	50	100**	100^{EPS}	0^{HC}	100^{HC}	100^{HC}
50	100	100^{EPS}	100^{EPS}	100^{HC}	100**	100**

Notes: cp. Table 4.1 and Table 4.2.

Table 4.3 shows the highest possible critical values c that produce the largest improvements. Recommendations are based on averaged results across the four convergence speeds and six Monte Carlo cases. For all pairs of T and N, except $N = 20$, the best results of nearly all criteria are achieved at $c = 100$. Single Monte Carlo outcomes are shown in Tables 4.5–4.10. The definite lower limit to optimize *size* and *power* is $c = 0$, and in most cases, setting c to a (very) high value is recommended. However, increasing $c > -1.645$ does not always improve *detection*, although high critical values are most often recommended. *sum* and *grade* mirror this trade-off and hence are suitable to function as decision criteria. Tables 4.12–4.17 show the corresponding results for the four convergence speeds α (not discussed here).

4.3.2 The Extended Phillips Sul vs. the Hierarchical Clustering Algorithm

EPS outcomes at the recommended critical value c_{rec} of criterion *grade* (see the last column of Table 4.3 and 4.5–4.10) were compared with Monte Carlo simulations performed using the HC algorithm. Analogous to the previous section, results presented here are calculated by simple average across the six MC specifications and four convergence speeds.

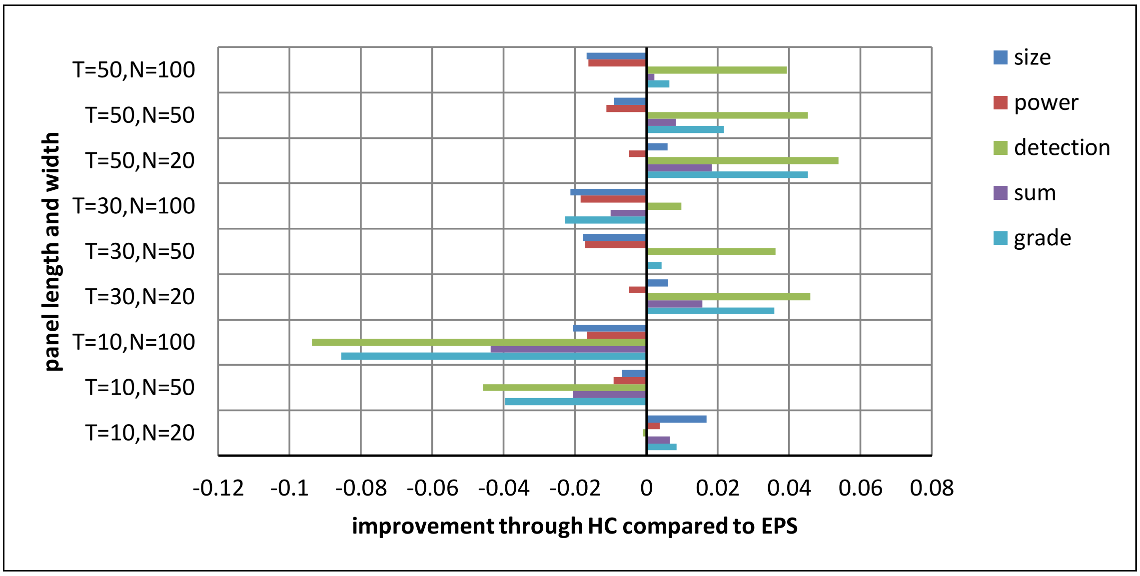

Fig. 4.2: All MCs: extended Philips Sul (EPS) and hierarchical clustering (HC) performance. Positive values indicate that HC is superior to EPS at the identified critical value.

Figure 4.2 shows HC and EPS performance for different panel sizes. EPS has an advantage for panels of length $T = 10$ and width $N = 50, 100$, whereas HC outperforms EPS procedure for narrow panels with $N = 20$. In the other cases, there is a trade-off between club *detection* rate against *size* and *power*. The *sum* and *grade* criteria show this trade-off weakens in favor of HC when $T = 50$.

The comparison of single MC simulations is shown in Figure 4.5. For the baseline scenario, MC 1, HC is superior to EPS in all cases except $T = 10$ and $N = 50, 100$. The HC benefit is more pronounced if the distance between the club specific growth paths δ_i increases (MC 3), and if diverging regions are added to the panel (MC 5). As the panel becomes more heterogeneous, by simulating five rather than two clubs (MC 4), HC is similar or slightly superior to EPS. On the other hand, EPS procedure similar or slightly superior if club specific growth paths, δ_i, lie close to each other (MC 2), and if ρ increases from 0.5 to 0.9. Detailed recommendations for preferred algorithms are provided as superscripts in Tables 4.3 and 4.5–4.17.

4.3.3 Improvement Scope

The vertical black lines at $c = 0$ in Figures 4.1 and 4.4 show EPS provides significant improvement compared to standard PS (2007,2009) methodology, which is shown in detail in Table 4.4 for the HC and EPS approaches at $c = 0$ and at c_{rec}.

Table 4.4: All MCs: absolute values and percentage improvements of criteria for different methods.

	size	power	detection	sum	grade
1) absolute values, using EPS with $c = 0$	0.152	0.877	0.760	0.828	0.572
2) absolute values, using EPS with c_{rec}	0.106	0.917	0.799	0.870	0.665
3) absolute values, using HC	0.113	0.907	0.809	0.867	0.663
improvement 1) to 2)	29.9%	4.6%	5.2%	5.0%	16.4%
improvement 2) to 3)	-6.6%	-1.1%	1.2%	-0.3%	-0.4%
improvement 1) to 3)	25.3%	3.4%	6.5%	4.7%	15.9%

Notes: cp. Table 4.1 and Table 4.2. To calculate the absolute values at c_{rec}, the recommended cs of the criterion *grade* as proposed in Table 4.3 were used for each specific pair of T, N, but across all convergence speeds α; subsequently, all values were averaged across T & N, and across all Monte Carlo specifications.

Cluster refinement by using c_{rec} rather than $c = 0$ is particularly strong for *size*, reducing from 0.152 to 0.106, an improvement of 30%. Due to larger denominators, percentage changes of the other criteria are somewhat smaller, but still significant. HC compared to EPS at $c =_{rec}$ provides only slightly improved *detection*, whereas *size* and *power* deteriorate, providing a nearly balanced effect for *sum* and *grade*.

Table 4.18 shows the corresponding results for the six Monte Carlo specifications. The EPS improvement at c_{rec} is particularly strong if transitional heterogeneity in the underlying panel is more persistent (higher ρ in MC 6). HC performs poorer than EPS at c_{rec}, although still significantly better than EPS at $c = 0$. In contrast, HC is advantageous for distant club specific growth paths (MC 3), and when the panel contains diverging regions (MC 5) or comparably more clubs (MC 4).

Thus, EPS at c_{rec} and HC perform significantly better than the standard PS (2007,2009) methodology. For heterogeneous panels containing many clubs or diverging regions, and for higher distances between growth paths, further improvement can be achieved using HC. However, caution is required, since EPS at c_{rec} also has significant strengths against HC. Thus, the recommendations in Tables 4.3 and 4.5–4.17 are advised when working with these clustering algorithms.

4.3.4 Dynamics

HC performs better for those cases where the increase in the critical value c leads to smaller EPS improvement (i.e., MC 3, MC 4, and MC 5). This can be taken as a weak indication that HC precision, and the partial superiority is the result of the weaknesses of the EPS procedure.

However, these outcomes do not clearly identify the performance difference source. Figure 4.3 shows the improvement according to panel length, T; panel width, N; and convergence speed, α. Values of each variable (T, N, α) were calculated as the simple average of all values of the other two variables, averaged across the six MCs.

Criteria *sum* and *grade* suggest that HC performs better with increasing T and α, but poorer with increasing N. The improvement with T is due to the significantly higher

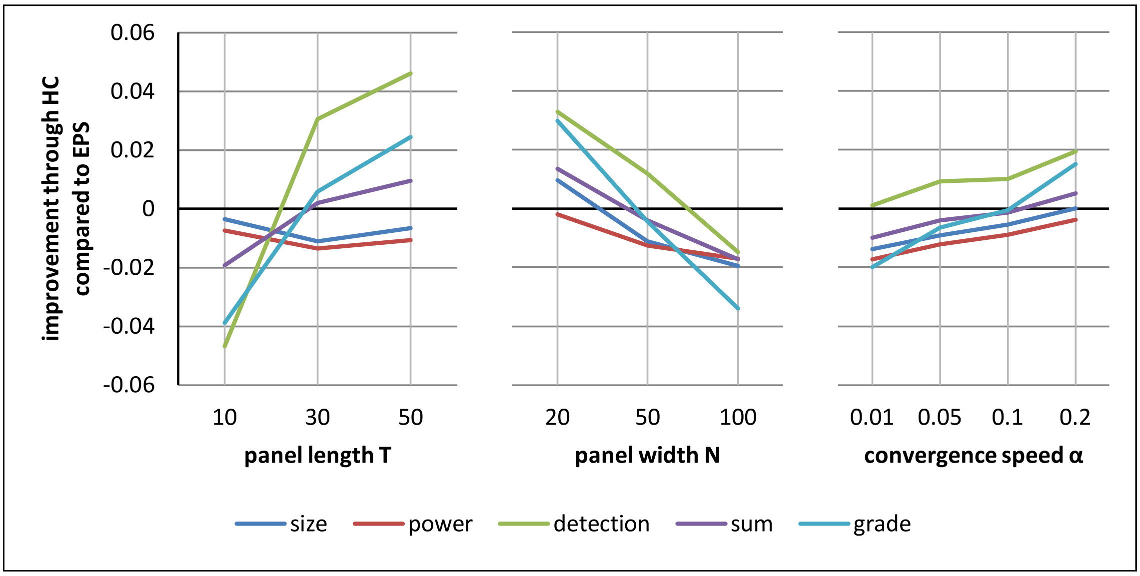

Fig. 4.3: All MCs: improvement dynamics for the extended Phillips Sul (EPS) and hierarchical clustering (HC) approaches.

detection, whereas *size* and *power* are largely constant. In case of N and α, the pathways of all five criteria show a similar slope.

Figures 4.6 and 4.7 show that the degree of improvement or deterioration (compared to MC 1) is increased for closer club specific growth paths (MC 3) and for panels including diverging regions (MC 5). Improvement dynamics with respect to N vary widely for the panels containing five clubs (MC 4), where HC performs increasingly better than EPS for higher N, as measured by *grade*.

4.4 Concluding Remarks

This study proposes a club merging algorithm which extends the Phillips and Sul (2007) club clustering algorithm. The club merging algorithm formalizes the club merging rule of Phillips and Sul (2009) in a similar fashion as the club merging algorithm proposed in Lyncker and Thoennessen (2017). As a general alternative, this study also proposes a hierarchical clustering algorithm based on the non-linear single factor model and the PS log t test. The HC algorithm is a more general method to cluster units based on the log t test. HC calculates a log t similarity matrix in the tradition of Ward (1963) and subsequently agglomerates the most similar units.

Monte Carlo methods were employed to target two objectives: first, to determine the performance of the PS algorithm when extended by incorporating the club merging algorithm proposed here; second, to compare the EPS methodology with the proposed HC algorithm.

For their original algorithm, PS (2007) recommended to set the critical value in the membership sieving to $c = 0$. However, simulations show that EPS methodology tends to perform best for high c. The EPS improvement is significant, with an average *size* improvement of 30% between $c = 0$ and c_{rec} across all specifications (i.e., all MCs, αs, Ts, and Ns).

HC generally performs better than EPS if the underlying panel is heterogeneous, in the sense that it contains a large number of clubs (here: five compared to two clubs). The HC advantage also manifests with increased distance between club growth paths, and inclusion of diverging regions. Average results across all Monte Carlo specifications suggest that HC is the better choice for narrow panels ($N = 20$), whereas EPS is superior for short and broader panels ($T = 10$, $N = 50, 100$).

Therefore, further studies using Phillips and Sul (2007) methodology are advised to employ the EPS clustering algorithm, which incorporates the club merging algorithm proposed here. For many cases the proposed hierarchical clustering algorithm may be an even better choice. Recommendations in Tables 4.3 and 4.5–4.17 provide methodological guidelines for future empirical research.

4.5 Appendix

Table 4.5: MC 1: recommended critical value c and recommended algorithm (average across αs).

T	N	size	power	detection	sum	grade
10	20	10**	10**	10^{HC}	10^{HC}	10**
10	50	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	100	50**	50**	100^{EPS}	50^{EPS}	50^{EPS}
30	20	1**	1^{EPS}	-1.645^{HC}	1^{HC}	1^{HC}
30	50	10^{EPS}	10^{EPS}	100^{HC}	10**	10**
30	100	5**	5**	5^{HC}	5**	5**
50	20	1**	1^{EPS}	-1.645^{HC}	1^{HC}	1^{HC}
50	50	5**	5**	0^{HC}	1^{HC}	1^{HC}
50	100	5**	5**	1^{HC}	5^{HC}	5^{HC}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.6: MC 2: recommended critical value c and recommended algorithm (average across αs).

T	N	size	power	detection	sum	grade
10	20	5**	5**	100^{EPS}	5^{EPS}	5^{EPS}
10	50	50^{EPS}	50^{EPS}	100^{EPS}	50^{EPS}	50^{EPS}
10	100	10^{EPS}	10^{EPS}	100^{EPS}	10^{EPS}	10^{EPS}
30	20	1^{EPS}	1^{EPS}	100^{HC}	1^{EPS}	1**
30	50	5^{EPS}	5^{EPS}	100^{EPS}	5^{EPS}	5^{EPS}
30	100	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
50	20	50^{EPS}	1^{EPS}	1^{HC}	1**	1**
50	50	1^{EPS}	5^{EPS}	5^{HC}	5^{EPS}	5^{EPS}
50	100	100^{EPS}	10^{EPS}	100**	10^{EPS}	10^{EPS}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.7: MC 3: recommended critical value c and recommended algorithm (average across αs).

T	N	size	power	detection	sum	grade
10	20	10**	10**	-1.645^{HC}	10^{HC}	10^{HC}
10	50	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	100	50**	50**	100^{EPS}	50^{EPS}	50^{EPS}
30	20	1**	1**	-1.645^{HC}	0^{HC}	0^{HC}
30	50	5**	5**	0^{HC}	1^{HC}	1^{HC}
30	100	100**	100**	1^{HC}	1^{HC}	1^{HC}
50	20	0^{HC}	1^{HC}	-1.645^{HC}	-1^{HC}	-1^{HC}
50	50	1**	1**	-1.645^{HC}	0^{HC}	0^{HC}
50	100	5**	5**	-1.645^{HC}	1^{HC}	1^{HC}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.8: MC 4: recommended critical value c and recommended algorithm (average across αs).

T	N	size	power	detection	sum	grade
10	20	0^{HC}	0^{HC}	10^{EPS}	0^{HC}	10^{EPS}
10	50	5^{HC}	5**	100^{HC}	100^{HC}	100^{HC}
10	100	100^{EPS}	10**	10^{HC}	10^{HC}	10^{HC}
30	20	0^{HC}	1**	100^{HC}	0^{HC}	0^{HC}
30	50	100^{EPS}	100**	0^{HC}	5^{HC}	5^{HC}
30	100	100^{EPS}	100**	100^{HC}	100^{HC}	100^{HC}
50	20	0^{HC}	0^{HC}	-1^{HC}	-1^{HC}	-1^{HC}
50	50	100**	100**	-1^{HC}	0^{HC}	0^{HC}
50	100	5**	5**	0^{HC}	1^{HC}	1^{HC}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.9: MC 5: recommended critical value c and recommended algorithm (average across αs).

T	N	size	power	detection	sum	grade
10	20	100^{HC}	100^{HC}	10^{HC}	10^{HC}	10^{HC}
10	50	50**	50**	100^{EPS}	100^{EPS}	50^{EPS}
10	100	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
30	20	1^{HC}	1**	0^{HC}	1^{HC}	1^{HC}
30	50	5**	5**	1^{HC}	10^{HC}	10^{HC}
30	100	100**	100**	5^{HC}	100^{HC}	100^{HC}
50	20	1^{HC}	1^{HC}	-1.645^{HC}	0^{HC}	0^{HC}
50	50	10**	10**	1^{HC}	1^{HC}	1^{HC}
50	100	5**	5**	1^{HC}	5^{HC}	5^{HC}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.10: MC 6: recommended critical value c and recommended algorithm (average across αs).

T	N	size	power	detection	sum	grade
10	20	100**	100**	100**	10**	10**
10	50	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	100	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
30	20	100^{EPS}	100^{EPS}	100^{HC}	100**	100**
30	50	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
30	100	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
50	20	100^{EPS}	100^{EPS}	1^{HC}	100^{EPS}	100^{EPS}
50	50	100^{EPS}	100^{EPS}	100^{HC}	100^{EPS}	100^{EPS}
50	100	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.11: All MCs: recommended critical value c and recommended algorithm.

T	N	α	size	power	detection	sum	grade
10	20	0.01	10^{HC}	10**	10**	10^{HC}	10**
10	20	0.05	100^{HC}	100**	10**	10**	10**
10	20	0.1	100^{HC}	100**	10**	10^{HC}	10**
10	20	0.2	100^{HC}	100**	10^{HC}	10^{HC}	10^{HC}
10	50	0.01	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.05	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.1	100**	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.2	50**	50**	100^{EPS}	50^{EPS}	50^{EPS}
10	100	0.01	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.05	50^{EPS}	50^{EPS}	100^{EPS}	50^{EPS}	50^{EPS}
10	100	0.1	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.2	100^{EPS}	50^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
30	20	0.01	1**	1**	5^{HC}	1^{HC}	5^{HC}
30	20	0.05	1**	1**	5^{HC}	1^{HC}	1^{HC}
30	20	0.1	1**	100**	1^{HC}	1^{HC}	1^{HC}
30	20	0.2	1**	10**	-1^{HC}	1^{HC}	1^{HC}
30	50	0.01	100^{EPS}	100^{EPS}	100^{HC}	100^{EPS}	100^{EPS}
30	50	0.05	100^{EPS}	100^{EPS}	100^{HC}	100**	100**
30	50	0.1	100^{EPS}	100^{EPS}	100^{HC}	100^{HC}	100^{HC}
30	50	0.2	100**	100**	0^{HC}	100^{HC}	100^{HC}
30	100	0.01	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
30	100	0.05	100^{EPS}	100^{EPS}	100^{HC}	100^{EPS}	100^{EPS}
30	100	0.1	100^{EPS}	100^{EPS}	100^{HC}	100^{EPS}	100^{EPS}
30	100	0.2	100**	100**	1^{HC}	100**	100**
50	20	0.01	100**	100^{EPS}	1^{HC}	1^{HC}	1^{HC}
50	20	0.05	100**	100**	-1^{HC}	1^{HC}	1^{HC}
50	20	0.1	1**	100**	-1^{HC}	1^{HC}	1^{HC}
50	20	0.2	1**	1**	-1.645^{HC}	0^{HC}	0^{HC}
50	50	0.01	100	100^{EPS}	1^{HC}	10^{HC}	10^{HC}
50	50	0.05	100**	100^{EPS}	0^{HC}	100^{HC}	100^{HC}
50	50	0.1	100**	100^{EPS}	0^{HC}	100^{HC}	100^{HC}
50	50	0.2	100**	100**	0^{HC}	1^{HC}	1^{HC}
50	100	0.01	100^{EPS}	100^{EPS}	100^{HC}	100**	100**
50	100	0.05	100^{EPS}	100^{EPS}	100^{HC}	100**	100**
50	100	0.1	100^{EPS}	100^{EPS}	1^{HC}	100^{HC}	100^{HC}
50	100	0.2	100**	100**	0^{HC}	100^{HC}	100^{HC}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.12: MC 1: recommended critical value c and recommended algorithm.

T	N	α	size	power	detection	sum	grade
10	20	0.01	10**	10**	100^{HC}	10**	10**
10	20	0.05	10**	10**	10**	10**	10**
10	20	0.1	10**	10**	10^{HC}	10^{HC}	10^{HC}
10	20	0.2	100**	100**	100^{HC}	100^{HC}	100^{HC}
10	50	0.01	100^{EPS}	100^{EPS}	10^{EPS}	100^{EPS}	100^{EPS}
10	50	0.05	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.1	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.2	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.01	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.05	100**	100**	10^{EPS}	100^{EPS}	100^{EPS}
10	100	0.1	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.2	50**	50**	100^{EPS}	50^{EPS}	50^{EPS}
30	20	0.01	1^{EPS}	1^{EPS}	100^{HC}	100^{HC}	100^{HC}
30	20	0.05	1^{EPS}	1^{EPS}	0^{HC}	1**	1**
30	20	0.1	1**	1**	-1^{HC}	1^{HC}	1^{HC}
30	20	0.2	1**	1**	-1.645^{HC}	1^{HC}	1^{HC}
30	50	0.01	5^{EPS}	5^{EPS}	5^{HC}	5^{EPS}	5^{EPS}
30	50	0.05	5^{EPS}	5^{EPS}	100^{HC}	5**	5**
30	50	0.1	100**	100**	1^{HC}	100^{HC}	100**
30	50	0.2	10**	10**	0^{HC}	10^{HC}	10^{HC}
30	100	0.01	100^{EPS}	100^{EPS}	5^{HC}	5^{EPS}	5^{EPS}
30	100	0.05	100^{EPS}	100^{EPS}	5^{HC}	5**	5**
30	100	0.1	5**	5**	5^{HC}	5**	5**
30	100	0.2	5**	5**	1**	5^{HC}	5^{HC}
50	20	0.01	100^{EPS}	1^{EPS}	-1.645^{HC}	1**	1**
50	20	0.05	1**	1**	-1.645^{HC}	1^{HC}	1^{HC}
50	20	0.1	1**	1**	-1.645^{HC}	0^{HC}	0^{HC}
50	20	0.2	0**	1**	-1.645^{HC}	0^{HC}	0^{HC}
50	50	0.01	100^{EPS}	100^{EPS}	1^{HC}	100^{HC}	1^{HC}
50	50	0.05	5**	5**	1^{HC}	5^{HC}	5^{HC}
50	50	0.1	5**	5**	-1^{HC}	1^{HC}	1^{HC}
50	50	0.2	1**	1**	0**	1^{HC}	1^{HC}
50	100	0.01	5^{EPS}	5^{EPS}	100^{HC}	5^{HC}	5^{HC}
50	100	0.05	100^{EPS}	100^{EPS}	0^{HC}	100^{HC}	100^{HC}
50	100	0.1	5**	5**	1^{HC}	5^{HC}	5^{HC}
50	100	0.2	5**	5**	-1**	5^{HC}	5^{HC}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.13: MC 2: recommended critical value c and recommended algorithm.

T	N	α	size	power	detection	sum	grade
10	20	0.01	10**	10**	100^{EPS}	10^{EPS}	10^{EPS}
10	20	0.05	5**	5**	100^{EPS}	5^{EPS}	5^{EPS}
10	20	0.1	5**	5**	5^{EPS}	5^{EPS}	5^{EPS}
10	20	0.2	5**	5**	100**	5^{EPS}	5**
10	50	0.01	5^{EPS}	5^{EPS}	100^{EPS}	10^{EPS}	10^{EPS}
10	50	0.05	100^{EPS}	100^{EPS}	10^{EPS}	10^{EPS}	10^{EPS}
10	50	0.1	100^{EPS}	100^{EPS}	10^{EPS}	100^{EPS}	100^{EPS}
10	50	0.2	50^{EPS}	50^{EPS}	100^{EPS}	50^{EPS}	50^{EPS}
10	100	0.01	10^{EPS}	5^{EPS}	100^{EPS}	10^{EPS}	10^{EPS}
10	100	0.05	10^{EPS}	10^{EPS}	100^{EPS}	10^{EPS}	10^{EPS}
10	100	0.1	10^{EPS}	10^{EPS}	10^{EPS}	10^{EPS}	10^{EPS}
10	100	0.2	50^{EPS}	50^{EPS}	100^{EPS}	50^{EPS}	50^{EPS}
30	20	0.01	1^{EPS}	1^{EPS}	1^{HC}	1^{EPS}	1^{EPS}
30	20	0.05	1^{EPS}	1^{EPS}	100**	1^{EPS}	1^{EPS}
30	20	0.1	1^{EPS}	1^{EPS}	100^{HC}	1^{EPS}	1**
30	20	0.2	1**	1**	100^{HC}	1^{HC}	1^{HC}
30	50	0.01	5^{EPS}	5^{EPS}	100^{EPS}	5^{EPS}	5^{EPS}
30	50	0.05	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
30	50	0.1	5^{EPS}	5^{EPS}	5**	5^{EPS}	5^{EPS}
30	50	0.2	5^{EPS}	5^{EPS}	100**	5^{EPS}	5^{EPS}
30	100	0.01	5^{EPS}	5^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
30	100	0.05	5^{EPS}	5^{EPS}	100^{EPS}	5^{EPS}	5^{EPS}
30	100	0.1	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
30	100	0.2	10^{EPS}	10^{EPS}	100**	10^{EPS}	10^{EPS}
50	20	0.01	1^{EPS}	1^{EPS}	100^{HC}	1^{EPS}	1^{EPS}
50	20	0.05	1^{EPS}	1^{EPS}	1^{HC}	1^{EPS}	1^{EPS}
50	20	0.1	1^{EPS}	1^{EPS}	1^{HC}	1**	1**
50	20	0.2	1**	1**	1**	1^{HC}	1^{HC}
50	50	0.01	5^{EPS}	5^{EPS}	100^{HC}	5^{EPS}	5^{EPS}
50	50	0.05	100^{EPS}	100^{EPS}	5^{HC}	5^{EPS}	5^{EPS}
50	50	0.1	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
50	50	0.2	5**	5**	100**	5**	5**
50	100	0.01	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
50	100	0.05	5^{EPS}	5^{EPS}	100**	100^{EPS}	100^{EPS}
50	100	0.1	100^{EPS}	5^{EPS}	100**	5^{EPS}	5^{EPS}
50	100	0.2	10**	10**	100**	10^{EPS}	10^{EPS}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.14: MC 3: recommended critical value c and recommended algorithm.

T	N	α	size	power	detection	sum	grade
10	20	0.01	10**	10**	5^{HC}	5^{HC}	5^{HC}
10	20	0.05	5**	5**	100^{HC}	10^{HC}	10^{HC}
10	20	0.1	5**	100**	-1.645^{HC}	10^{HC}	10^{HC}
10	20	0.2	10**	10**	-1.645^{HC}	10^{HC}	10^{HC}
10	50	0.01	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.05	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.1	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.2	10**	10**	100**	100^{HC}	100^{HC}
10	100	0.01	100**	100**	10^{EPS}	100^{EPS}	100^{EPS}
10	100	0.05	50**	50**	100^{EPS}	50^{EPS}	50^{EPS}
10	100	0.1	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.2	50**	50**	100^{EPS}	50**	50**
30	20	0.01	1**	100**	-1.645^{HC}	0^{HC}	0^{HC}
30	20	0.05	1**	1**	-1.645^{HC}	0^{HC}	0^{HC}
30	20	0.1	0**	1**	-1.645^{HC}	0^{HC}	0^{HC}
30	20	0.2	0**	0**	-1.645^{HC}	-1^{HC}	-1^{HC}
30	50	0.01	5**	5**	0^{HC}	5^{HC}	5^{HC}
30	50	0.05	5**	5**	-1.645^{HC}	5^{HC}	5^{HC}
30	50	0.1	1**	1**	-1.645^{HC}	0^{HC}	0^{HC}
30	50	0.2	1**	1**	-1^{HC}	0^{HC}	0^{HC}
30	100	0.01	100**	100**	100^{HC}	100^{HC}	100^{HC}
30	100	0.05	100**	100**	1^{HC}	5^{HC}	5^{HC}
30	100	0.1	100**	100**	0^{HC}	1^{HC}	1^{HC}
30	100	0.2	1**	1**	-1^{HC}	1^{HC}	1^{HC}
50	20	0.01	5^{HC}	100^{HC}	-1.645^{HC}	-1^{HC}	-1^{HC}
50	20	0.05	0^{HC}	1^{HC}	-1.645^{HC}	0^{HC}	0^{HC}
50	20	0.1	0^{HC}	0^{HC}	-1.645^{HC}	-1^{HC}	-1^{HC}
50	20	0.2	-1**	0**	-1.645**	-1^{HC}	-1^{HC}
50	50	0.01	100**	5**	-1.645^{HC}	0^{HC}	0^{HC}
50	50	0.05	1**	1**	-1.645^{HC}	0^{HC}	0^{HC}
50	50	0.1	1**	1**	-1.645^{HC}	0^{HC}	0^{HC}
50	50	0.2	0**	1**	-1**	0**	0**
50	100	0.01	5**	5**	-1.645^{HC}	1^{HC}	1^{HC}
50	100	0.05	5**	5**	-1.645^{HC}	0^{HC}	0^{HC}
50	100	0.1	1**	1**	0^{HC}	1^{HC}	1^{HC}
50	100	0.2	1**	1**	-1**	1**	1**

Notes: cp. Table 4.1 and Table 4.2.

Table 4.15: MC 4: recommended critical value c and recommended algorithm.

T	N	α	size	power	detection	sum	grade
10	20	0.01	0^{HC}	0^{HC}	100^{EPS}	0^{HC}	100^{EPS}
10	20	0.05	0^{HC}	0**	5^{EPS}	0^{HC}	5**
10	20	0.1	0^{HC}	1^{HC}	100^{EPS}	100^{HC}	100^{EPS}
10	20	0.2	0^{HC}	0^{HC}	10^{EPS}	10^{HC}	10**
10	50	0.01	100^{HC}	100**	-1.645**	5^{HC}	5**
10	50	0.05	100^{HC}	100**	-1.645^{HC}	100^{HC}	100^{HC}
10	50	0.1	5^{HC}	5**	100^{HC}	5^{HC}	100^{HC}
10	50	0.2	10^{HC}	10**	100^{HC}	10^{HC}	100^{HC}
10	100	0.01	10^{EPS}	10**	-1^{HC}	10^{HC}	10^{HC}
10	100	0.05	10^{EPS}	10**	10^{HC}	10^{HC}	10^{HC}
10	100	0.1	10^{EPS}	10^{EPS}	10^{HC}	10^{HC}	10^{HC}
10	100	0.2	100^{EPS}	100**	100^{HC}	100^{HC}	100^{HC}
30	20	0.01	0^{HC}	1^{HC}	100^{HC}	100^{HC}	100^{HC}
30	20	0.05	1^{HC}	1**	100^{HC}	5^{HC}	5^{HC}
30	20	0.1	0^{HC}	0**	100^{HC}	0^{HC}	0^{HC}
30	20	0.2	0^{HC}	0**	-1^{HC}	-1^{HC}	-1^{HC}
30	50	0.01	5^{EPS}	5**	100^{HC}	100**	100^{HC}
30	50	0.05	100^{EPS}	100**	5^{HC}	5^{HC}	5^{HC}
30	50	0.1	5**	5**	0^{HC}	100^{HC}	100^{HC}
30	50	0.2	1^{HC}	1**	-1^{HC}	0^{HC}	0^{HC}
30	100	0.01	100^{EPS}	100^{EPS}	100^{HC}	100^{HC}	100^{HC}
30	100	0.05	100^{EPS}	100^{EPS}	100^{HC}	100^{HC}	100^{HC}
30	100	0.1	100^{EPS}	100**	5^{HC}	5^{HC}	5^{HC}
30	100	0.2	5**	5**	0^{HC}	1^{HC}	1^{HC}
50	20	0.01	0^{HC}	0^{HC}	1^{HC}	1^{HC}	1^{HC}
50	20	0.05	0^{HC}	1^{HC}	-1^{HC}	1^{HC}	1^{HC}
50	20	0.1	0^{HC}	0^{HC}	-1^{HC}	-1^{HC}	-1^{HC}
50	20	0.2	0^{HC}	0**	-1.645^{HC}	-1^{HC}	-1^{HC}
50	50	0.01	5**	5**	-1^{HC}	1^{HC}	0^{HC}
50	50	0.05	100^{HC}	100**	-1^{HC}	0^{HC}	0^{HC}
50	50	0.1	1^{HC}	1**	-1.645^{HC}	0^{HC}	0^{HC}
50	50	0.2	0**	1**	-1.645^{HC}	-1^{HC}	-1^{HC}
50	100	0.01	5^{EPS}	5**	0^{HC}	1^{HC}	1^{HC}
50	100	0.05	100**	5**	0^{HC}	1^{HC}	1^{HC}
50	100	0.1	5**	5**	0^{HC}	1^{HC}	0^{HC}
50	100	0.2	1**	1**	-1^{HC}	0^{HC}	0^{HC}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.16: MC 5: recommended critical value c and recommended algorithm.

T	N	α	size	power	detection	sum	grade
10	20	0.01	1^{HC}	1^{HC}	100^{HC}	10^{HC}	10^{HC}
10	20	0.05	100**	100**	100**	100^{HC}	100^{HC}
10	20	0.1	5^{HC}	5^{HC}	100^{HC}	5^{HC}	5^{HC}
10	20	0.2	100^{HC}	100^{HC}	10^{HC}	10^{HC}	10^{HC}
10	50	0.01	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.05	100**	100**	10^{EPS}	100^{EPS}	100^{EPS}
10	50	0.1	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.2	50**	50**	100^{EPS}	50^{EPS}	50^{EPS}
10	100	0.01	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.05	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.1	100**	100**	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.2	50**	50**	100^{EPS}	50^{EPS}	50^{EPS}
30	20	0.01	1^{HC}	1**	-1.645^{HC}	1^{HC}	1^{HC}
30	20	0.05	1**	1**	0^{HC}	1^{HC}	1^{HC}
30	20	0.1	100^{HC}	100**	0^{HC}	0^{HC}	1^{HC}
30	20	0.2	1**	1**	0^{HC}	0^{HC}	0^{HC}
30	50	0.01	100^{EPS}	100^{EPS}	1^{HC}	100^{HC}	100^{HC}
30	50	0.05	100**	100**	1^{HC}	100^{HC}	100^{HC}
30	50	0.1	5**	5**	1^{HC}	100^{HC}	100^{HC}
30	50	0.2	5**	5**	1^{HC}	1^{HC}	1^{HC}
30	100	0.01	100^{EPS}	100^{EPS}	5^{HC}	100^{HC}	100**
30	100	0.05	10**	10**	5^{HC}	5^{HC}	5^{HC}
30	100	0.1	10**	10**	5^{HC}	10^{HC}	10^{HC}
30	100	0.2	100**	100**	100^{HC}	100^{HC}	100^{HC}
50	20	0.01	1^{HC}	1^{HC}	-1.645^{HC}	1^{HC}	1^{HC}
50	20	0.05	100^{HC}	100^{HC}	-1.645^{HC}	1^{HC}	1^{HC}
50	20	0.1	5^{HC}	5^{HC}	0^{HC}	0^{HC}	0^{HC}
50	20	0.2	1**	1**	-1.645^{HC}	0^{HC}	0^{HC}
50	50	0.01	5**	5**	1^{HC}	1^{HC}	1^{HC}
50	50	0.05	10**	10**	0^{HC}	1^{HC}	1^{HC}
50	50	0.1	100**	100**	1^{HC}	1^{HC}	1^{HC}
50	50	0.2	1**	1**	0^{HC}	1^{HC}	1^{HC}
50	100	0.01	100**	100**	1^{HC}	1^{HC}	1^{HC}
50	100	0.05	100**	100**	1^{HC}	1^{HC}	1^{HC}
50	100	0.1	5**	5**	1^{HC}	5^{HC}	5^{HC}
50	100	0.2	5**	5**	5^{HC}	5^{HC}	5^{HC}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.17: MC 6: recommended critical value c and recommended algorithm.

T	N	α	size	power	detection	sum	grade
10	20	0.01	100**	100**	5**	100**	100**
10	20	0.05	10**	10**	10^{EPS}	10**	10**
10	20	0.1	100**	100**	10^{EPS}	100**	100**
10	20	0.2	100**	100**	10**	10**	10**
10	50	0.01	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.05	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.1	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	50	0.2	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.01	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.05	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.1	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
10	100	0.2	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
30	20	0.01	100^{EPS}	100^{EPS}	5^{HC}	100**	100**
30	20	0.05	100^{EPS}	100^{EPS}	5^{HC}	100**	100**
30	20	0.1	10^{EPS}	100^{EPS}	100^{HC}	10**	10**
30	20	0.2	10**	100^{EPS}	100^{HC}	10**	10**
30	50	0.01	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
30	50	0.05	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
30	50	0.1	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
30	50	0.2	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
30	100	0.01	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
30	100	0.05	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
30	100	0.1	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
30	100	0.2	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
50	20	0.01	100^{EPS}	100^{EPS}	100^{HC}	100^{EPS}	100^{EPS}
50	20	0.05	5^{EPS}	5^{EPS}	5^{HC}	5**	5**
50	20	0.1	100^{EPS}	100^{EPS}	1^{HC}	100^{EPS}	100^{EPS}
50	20	0.2	5**	5^{EPS}	-1.645^{HC}	5^{HC}	100^{HC}
50	50	0.01	100^{EPS}	100^{EPS}	10^{HC}	10^{EPS}	10^{EPS}
50	50	0.05	100^{EPS}	100^{EPS}	100^{HC}	100^{EPS}	100^{EPS}
50	50	0.1	100^{EPS}	100^{EPS}	100^{HC}	100^{EPS}	100^{EPS}
50	50	0.2	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
50	100	0.01	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
50	100	0.05	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}
50	100	0.1	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}	100^{EPS}
50	100	0.2	100^{EPS}	100^{EPS}	100**	100^{EPS}	100^{EPS}

Notes: cp. Table 4.1 and Table 4.2.

Table 4.18: MC 1 to MC 6: absolute values and percentage improvements of criteria for different methods.

	size	power	detection	sum	grade
MC 1					
1) absolute values, using EPS with $c = 0$	0.102	0.900	0.875	0.891	0.708
2) absolute values, using EPS with c_{rec}	0.064	0.938	0.909	0.928	0.799
3) absolute values, using HC	0.070	0.931	0.912	0.924	0.793
improvement 1) to 2)	37.1%	4.2%	3.9%	4.1%	12.8%
improvement 2) to 3)	-8.5%	-0.8%	0.2%	-0.4%	-0.8%
improvement 1) to 3)	31.8%	3.4%	4.1%	3.7%	11.9%
MC 2					
1) absolute values, using EPS with $c = 0$	0.248	0.755	0.659	0.722	0.348
2) absolute values, using EPS with c_{rec}	0.174	0.827	0.737	0.797	0.501
3) absolute values, using HC	0.202	0.799	0.703	0.767	0.447
improvement 1) to 2)	29.7%	9.6%	11.8%	10.3%	43.8%
improvement 2) to 3)	-15.6%	-3.4%	-4.5%	-3.7%	-10.7%
improvement 1) to 3)	18.7%	5.9%	6.7%	6.2%	28.4%
MC 3					
1) absolute values, using EPS with $c = 0$	0.048	0.956	0.881	0.929	0.805
2) absolute values, using EPS with c_{rec}	0.035	0.968	0.898	0.944	0.841
3) absolute values, using HC	0.031	0.970	0.915	0.951	0.862
improvement 1) to 2)	27.7%	1.3%	2.0%	1.6%	4.5%
improvement 2) to 3)	9.8%	0.1%	1.9%	0.8%	2.5%
improvement 1) to 3)	34.8%	1.5%	3.9%	2.3%	7.2%
MC 4					
1) absolute values, using EPS with $c = 0$	0.184	0.957	0.528	0.767	0.448
2) absolute values, using EPS with c_{rec}	0.150	0.965	0.549	0.788	0.483
3) absolute values, using HC	0.135	0.967	0.623	0.818	0.551
improvement 1) to 2)	18.2%	0.9%	3.9%	2.7%	7.8%
improvement 2) to 3)	10.1%	0.2%	13.6%	3.9%	14.0%
improvement 1) to 3)	26.5%	1.0%	18.0%	6.7%	22.9%
MC 5					
1) absolute values, using EPS with $c = 0$	0.147	0.871	0.820	0.848	0.601
2) absolute values, using EPS with c_{rec}	0.115	0.900	0.856	0.880	0.677
3) absolute values, using HC	0.111	0.903	0.875	0.889	0.702
improvement 1) to 2)	21.4%	3.3%	4.4%	3.8%	12.7%
improvement 2) to 3)	4.2%	0.4%	2.3%	1.0%	3.7%
improvement 1) to 3)	24.7%	3.7%	6.8%	4.9%	16.9%
MC 6					
1) absolute values, using EPS with $c = 0$	0.182	0.822	0.795	0.812	0.520
2) absolute values, using EPS with c_{rec}	0.099	0.905	0.845	0.883	0.691
3) absolute values, using HC	0.132	0.870	0.825	0.854	0.620
improvement 1) to 2)	45.5%	10.0%	6.3%	8.8%	33.0%
improvement 2) to 3)	-33.5%	-3.8%	-2.4%	-3.3%	-10.3%
improvement 1) to 3)	27.3%	5.8%	3.8%	5.2%	19.3%

Notes: cp. Table 4.1 and Table 4.2. To calculate the absolute values at c_{rec}, the recommended cs of the criterion *grade* as proposed in Table 4.5 to 4.10 were used for each specific pair of T, N, but across all convergence speeds α; subsequently, all values were averaged across T and N.

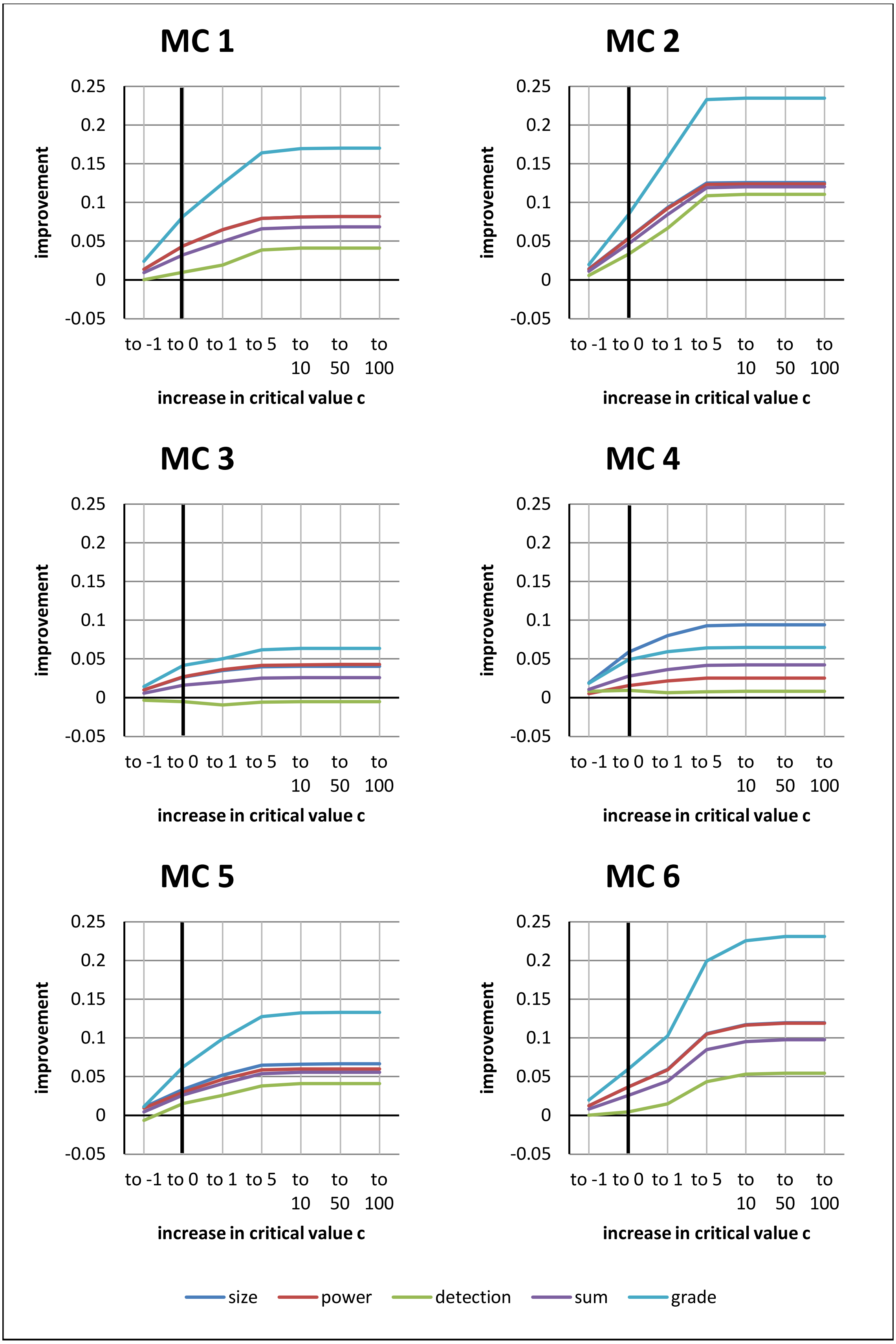

Fig. 4.4: MC 1 to MC 6: extended Phillips Sul (EPS) performance with differing critical value.

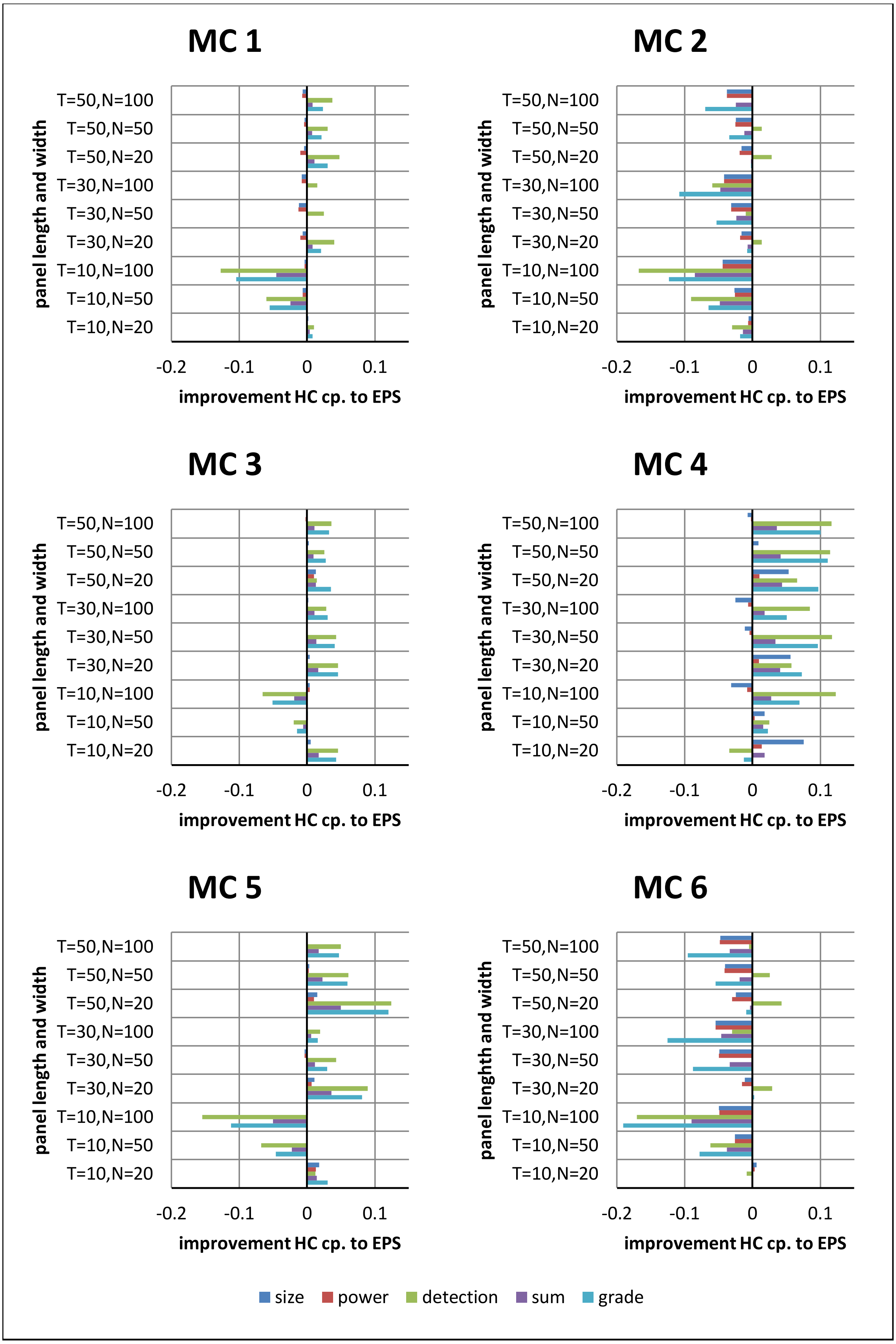

Fig. 4.5: MC 1 to MC 6: extended Phillips Sul (EPS) and hierarchical clustering (HC) performance.

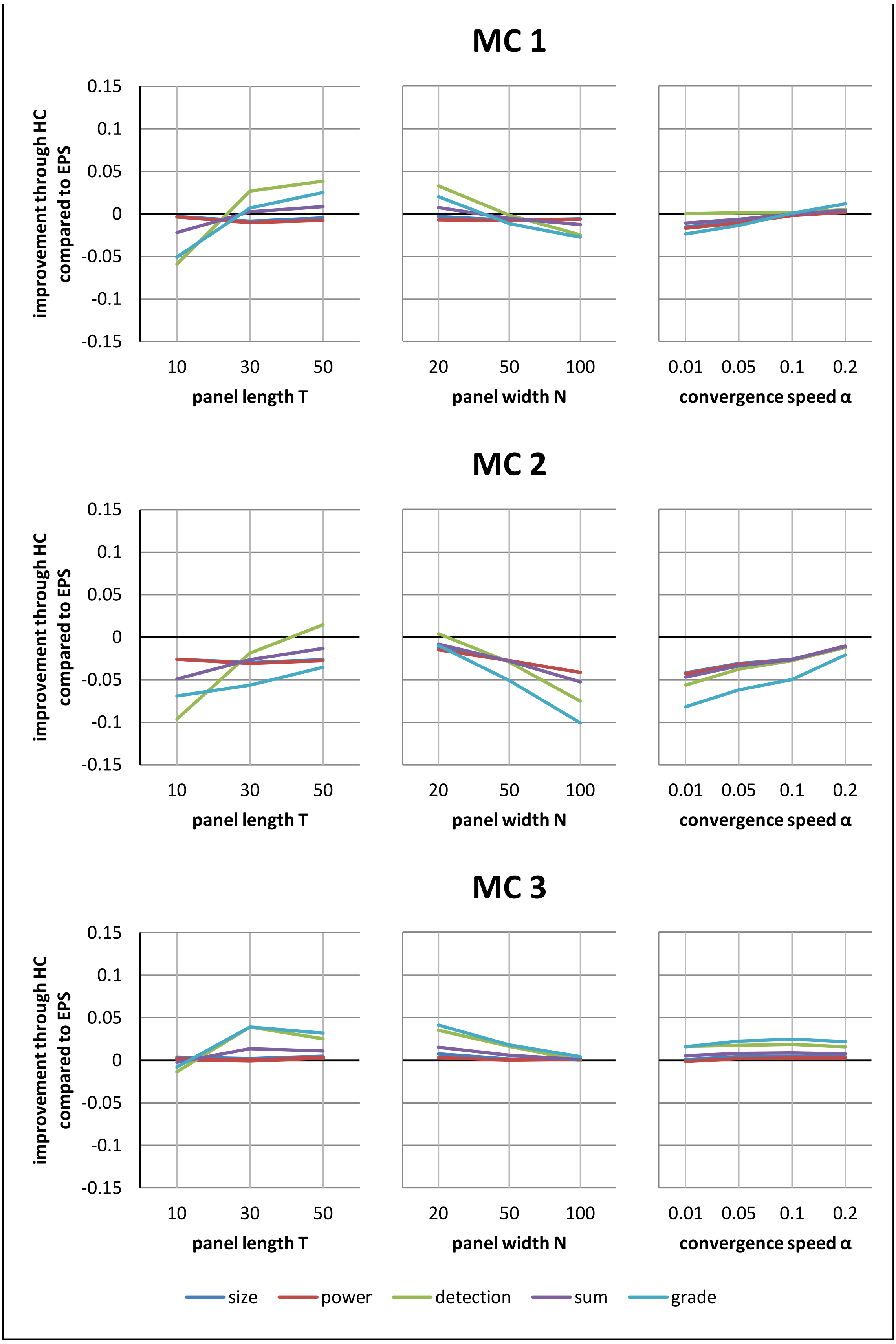

Fig. 4.6: MC 1 to MC 3: extended Phillips Sul (EPS) and hierarchical clustering (HC) improvement dynamics.

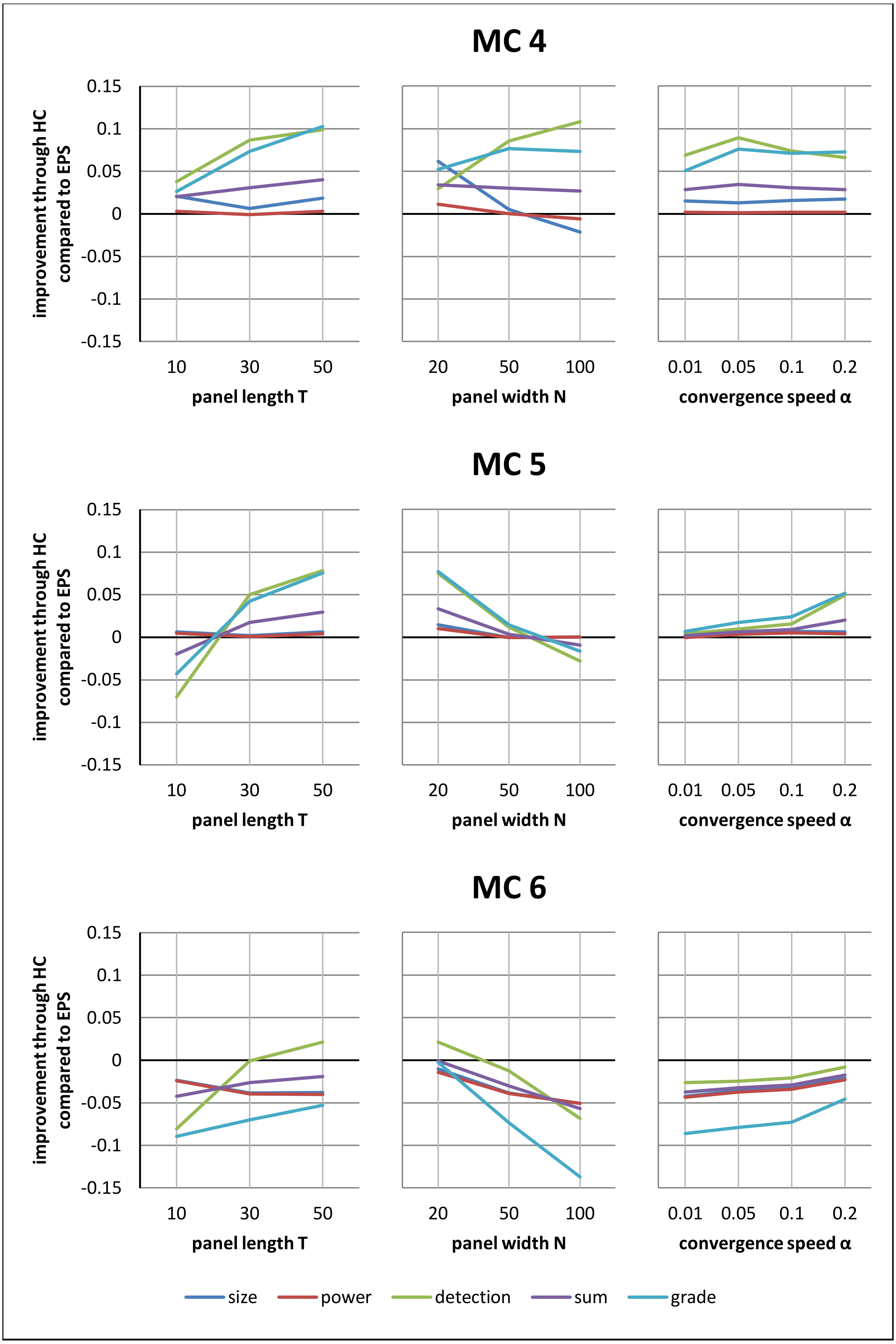

Fig. 4.7: MC 4 to MC 6: extended Phillips Sul (EPS) and hierarchical clustering (HC) improvement dynamics.

Chapter 5

Convergence in European Regions: Trends, Speed, and Stability

The contribution of this paper is twofold. First, using the Phillips–Sul log t test, a procedure is proposed that identifies the statistically most stable club clusters of regions (club cores). Second, the standard Phillips–Sul clustering algorithm, a hierarchical clustering algorithm, and a club core identification procedure are applied to income per capita data for a panel of 68 NUTS-1 regions in Western Europe. Results for 1980–2011 suggest that there are a maximum of six convergence clubs in the EU-15. An investigation of the club cores reveals that convergence speeds within the six clubs have decreased over the last 13 years, most probably because of fragmentation of convergence clubs over the same period. These findings indicate that regional heterogeneity and the role of club convergence have increased in the EU-15. Given that the trends changed before the Euro and financial crises, the results suggest that European cohesion policy has not been able to achieve convergence in the EU-15.

JEL classification: C23, C50, F02, O47, R11

Keywords: club convergence, regional development, log t test

5.1 Introduction

Income convergence across European regions has been a political goal since it was first declared in the preamble of the 1957 treaty establishing the European Economic Community (EEC). The 1987 Single European Act specified this objective, stating that '[...] the Community shall aim at reducing disparities between the various regions and the backwardness of the least-favoured regions' (European Communities, 1987). Since then, a substantial part of the EU budget has been devoted to European cohesion policy. In the EU multiannual financial framework for 2014–2020, one third of the budget is scheduled for economic, social, and territorial cohesion (European Commission, 2014) .

Cohesion policy is implicitly based on the expectation that conditional and ultimately absolute convergence across European regions can be achieved. In this sense, if conditional income convergence prevailed in Europe, further efforts to harmonize structural conditions across countries and regions would be required. Recent empirical research, however, indicates that club convergence actually explains much of the European growth pattern (Fritsche and Kuzin, 2011; Bartkowska and Riedl, 2012; Borsi and Metiu, 2015). The club convergence hypothesis postulates that units converge to the same steady-state growth path if their initial conditions are in the same basin of attraction (Galor, 1996). If club convergence exists, the goal of absolute convergence is virtually unattainable (unless club-specific growth paths converge to each other), even if political measures eliminate structural differences. The policy response in this case can be either implementation of an income-compensating transfer mechanism or 'politically sensitive handling of a multi-speed Europe', as argued by Lyncker and Thoennessen (2017).

This paper extends the literature on regional club convergence in Europe, drawing on the Phillips–Sul (PS) log t test and their club clustering algorithm (Phillips and Sul, 2007). The contribution is methodological and empirical in nature. Section 5.4.2 describes an extension of the PS procedure that identifies both the maximum number of clubs within a panel and the core regions of each club (regions within a club that constitute the most statistically significant cluster). The procedure allows reliable inference about the stability of convergence clubs and the respective club convergence speed. Empirically, application of the standard clustering procedure and the proposed methodological innovation to a panel of 68 NUTS-1 regions fills a gap in the literature, since previous studies have applied the PS method to either NUTS-2 or national data.

Results for the standard PS procedure point to the presence of three to four income clubs in the EU-15. This finding fits between the number of clubs identified at the national level (Apergis et al., 2010; Fritsche and Kuzin, 2011; Monfort et al., 2013, 1–3 clubs) and at the NUTS-2 level (Bartkowska and Riedl, 2012; Lyncker and Thoennessen, 2017, 4–6 clubs).

However, the detection of six very stable club cores according to the club core identification (CCI) procedure demonstrates that the standard PS methodology underestimates the degree of growth heterogeneity in Europe.

Over the whole time period, club convergence occurred among core regions at very fast rates. Nevertheless, an analysis of subperiods reveals that the convergence speed in medium- and high-income club cores has dwindled, with significant trend breaks in 1997 and 2003. This decline in club convergence speed can be explained by recent fragmentation of existing clubs into a range of new clubs, indicating a surge in heterogeneity across European NUTS-1 regions. Hence, the role of club convergence in regional growth patterns in Western Europe is not waning but increasing.

The remainder of the paper is organized as follows. Section 5.2 provides a short overview of the empirical literature on convergence with a focus on club convergence in European regions. The estimation strategy, which also comprises the CCI procedure, is outlined in Section 5.3. Results are provided in Section 5.4, followed by a summary and concluding remarks in Section 5.5.

5.2 Literature Review

The empirical literature on convergence began with a seminal paper by Baumol (1986), who was the first to test for a negative relationship between initial income and subsequent growth rates. Formal derivations of this Solow relationship, which became known as β convergence, were described by Barro and Sala-i Martin (1992) and Mankiw et al. (1992). Their concept of conditional convergence implies that convergence holds in the case of similar structural characteristics. A panel specification taking into account potential differences in the aggregate production functions was proposed by Islam (1995). Bernard and Durlauf (1995) developed a time-series specification that uses unit roots to test for the convergence relationship. Quah (1993, 1996) extended this methodology with a distributional framework. More recently, Bayesian model averaging techniques have been used to investigate income convergence (Crespo Cuaresma and Feldkircher, 2013; Cuaresma et al., 2014).

Here, we refer to the notion of club convergence. As outlined above, the club convergence hypothesis predicts convergence to the same steady-state growth path if initial conditions are in the same basin of attraction (Galor, 1996). Azariadis and Drazen (1990) showed that multiple steady states might prevail even if structural characteristics are similar. Azariadis (1996) argued that historical differences or thresholds might cause convergence clubs in the case of non-convexities in human capital accumulation. Various methods have been proposed to empirically test for club convergence. Durlauf and Johnson (1995) used a regression tree approach for national data and rejected a common linear growth path in favor of multiple growth regimes. Desdoigts (1999) and Hobijn and Franses (2000) applied cluster techniques and could not reject the validity of the club convergence hypothesis for national data. Canova (2004) proposed a predictive density approach and detected club convergence at a regional level. Regional convergence clubs were also found by Dall'Erba et al. (2008) and Ramajo et al. (2008) in a spatial econometric framework.

To detect convergence clubs in this study, the nonlinear time-varying factor model proposed by Phillips and Sul (2007) is applied. The PS log t test can identify convergence even in the presence of transitional and individual heterogeneity. Moreover, since growth is simply explained by one common and one individual factor, potential problems with omitted variable bias do not apply. To detect convergence clubs, Phillips and Sul (2007) proposed a clustering algorithm and a subsequent club merging procedure Phillips and Sul (2009). Lyncker and Thoennessen (2017) developed two post-clustering algorithms to finalize club formation in ambiguous cases. A competing clustering algorithm was proposed and tested by Lyncker (2016). Bartkowska and Riedl (2012) used an ordered logit model to test the validity of the club convergence hypothesis.

The PS procedure has been used by a few authors to detect club convergence in national income in Europe. Apergis et al. (2010) and Fritsche and Kuzin (2011) found one to three convergence clubs for income per capita in the EU-15 for different periods between 1960 and 2006. Borsi and Metiu (2015) considered the eastern European countries that joined the EU more recently and found four convergence clubs, with a clear division between (north-)west and (south-)east. Using data for income per worker, Monfort et al. (2013) found two convergence clubs and a core–periphery cluster in the EU-15. In a shorter EU-25 panel, they also detected two convergence clubs, and the geographic clustering switched to a west–east division. For a sample of 206 NUTS-2 regions over the period 1990–2002, Bartkowska and Riedl (2012) detected six convergence clubs in income per worker. Lyncker and Thoennessen (2017) used a panel of 194 NUTS-2 regions over the period 1980–2011 and identified four convergence clubs with a clear north–south division and a strong metropolitan effect. The latter two studies confirmed the important role of initial conditions for club formation. Our study contributes to this strand of literature and extends the scope of analysis to the NUTS-1 level.

Other strategies have been applied to detect regional convergence clubs in Europe. Canova (2004) used a predictive density approach and detected four convergence clubs in a sample of 144 NUTS-2 regions. Ertur et al. (2006) estimated a spatial error model for spatial regimes among 138 NUTS-1 and NUTS-2 regions over the period 1980–1995 and found that convergence was absent in the northern regime and weak in the southern regime.

Fischer and Stirböck (2006) followed the regression tree approach of Durlauf and Johnson (1995), but modeled spatial heterogeneity instead of simple heterogeneity. Using a sample of 256 NUTS-2 regions over the period 1995–2000, they obtained evidence of club convergence, with the formation of two regimes. Basile (2008) used a spatial Durban model for a sample of 155 NUTS-2 regions over the period 1988–2000 and identified at least three convergence clubs with different convergence speeds. Ramajo et al. (2008) used spatial econometric techniques for a sample of 163 NUTS-2 regions over the period 1981–1996. They found that regions in Ireland, Greece, Portugal, and Spain converged separately and at a different speed compared to the remaining regions. Dall'Erba et al. (2008) applied a spatial econometric framework and found four convergence clubs in a sample of 255 NUTS-2 regions.

5.3 Estimation Strategy

5.3.1 PS Factor Model

We use the methodological framework developed by Phillips and Sul (2007). The starting point of the PS framework is the following neoclassical growth regression, which allows for individual heterogeneity and transitional behavior (Phillips and Sul, 2009):

$$\log y_{it} = \log \tilde{y}_i^* + \log A_{i0} + [\log \tilde{y}_{i0} - \log \tilde{y}_i^*]e^{-\beta_{it} t} + x_{it} t, \tag{5.1}$$

where $\log \tilde{y}_{i0}$ is the initial level of log per capita income and $\log \tilde{y}_i^*$ is the corresponding steady-state level. $\log A_{i0}$ denotes the initial log of technology. x_{it} captures the individual and transitional growth rate of the dependent variable and β_{it} the corresponding convergence speed. With $a_{it} = \log \tilde{y}_i^* + \log A_{i0} + [\log \tilde{y}_{i0} - \log \tilde{y}_i^*]e^{-\beta_{it} t}$, Equation (5.1) can be expressed as

$$\log y_{it} = a_{it} + x_{it} t, \tag{5.2}$$

where

$$a_{it} \to \log \tilde{y}_i^* + \log A_{i0} \text{ for all } i \text{ as } t \to \infty. \tag{5.3}$$

Therefore, as t increases, the evolution of $\log y_{it}$ is increasingly determined by the growth path $x_{it} t$. Phillips and Sul (2007) presumed that this growth path contains some common elements for a certain set of countries. Hence, they decomposed the variable of interest y_{it} into a common growth path μ_t and an individual transition factor δ_{it}, which measures the share of μ_t for unit i. Equation (5.2) can be transformed to the form

$$\log y_{it} = \frac{a_{it} + x_{it}t}{\mu_t} \cdot \mu_t = \delta_{it}\mu_t. \tag{5.4}$$

In this factor representation, the transition parameter δ_{it} incorporates the convergence speed β_{it}, technological progress x_{it}, initial technology A_{i0}, and steady-state level $\tilde{y}_i^*$. To estimate δ_{it}, Phillips and Sul (2009) calculated a relative transition coefficient h_{it}, which measures transition of unit i at time t in relation to the panel average:

$$h_{it} = \frac{\delta_{it}\mu_t}{N^{-1}\sum_{i=1}^{N}\delta_{it}\mu_t}. \tag{5.5}$$

Growth convergence holds if the individual transition factor δ_{it} ultimately converges to a common δ for all i as $t \to \infty$. In terms of relative transition coefficients, convergence requires the following:

$$h_{it} \to 1 \text{ for all } i \text{ as } t \to \infty. \tag{5.6}$$

The PS factor representation hence allows modeling of transition economies whose short-run growth paths deviate from their long-run trends.

5.3.2 PS log t test

Using the factor model in Equation (5.4), Phillips and Sul (2007) proposed a test for income convergence that refers to the concept of conditional σ convergence. The PS log t test assesses whether the distance from the common growth path μ ultimately decreases over time. For this purpose, the cross-sectional variance of the relative transition parameter h_{it}, H_t, is calculated:

$$H_t = N^{-1}\sum_{i=1}^{N}(h_{it} - 1)^2. \tag{5.7}$$

Analogous to Equation (5.6), convergence requires that the cross-sectional variance diminishes over time:

$$H_t = N^{-1}\sum\nolimits_{i=1}^{N}(h_{it} - 1)^2 \to 0 \text{ as } t \to \infty. \tag{5.8}$$

As shown in Equation (5.4), any individual and transitional heterogeneity is incorporated in the coefficient δ_{it}. To capture this, Phillips and Sul (2007) proposed the following semiparametric model of δ_{it}:

$$\delta_{it} = \delta_i + \sigma_i\xi_{it}L(t)^{-1}t^{-\alpha}, \tag{5.9}$$

where δ_i measures the time-invariant part of the factor loading δ_{it}, σ_i is an idiosyncratic scale parameter, ξ_{it} is a random error variable that is $iid(0,1)$ across i and is weakly autocorrelated, $L(t)$ is a slowly varying increasing function, and α is a decay parameter that captures the speed of convergence. It holds that

$$\delta_{it} \to \delta_i \text{ for all } i \text{ as } t \to \infty, \tag{5.10}$$

so every unit converges to its specific growth path $\delta_i \mu_t$ over time. Moreover, a set of units converge to each other if

$$\delta_{it} \to \delta \text{ for all } i \text{ as } t \to \infty. \tag{5.11}$$

This allows us to set up a null hypothesis of convergence H_0 and to test it against its alternative H_A:

$$H_0 : \delta_i = \delta \text{ and } \alpha \geq 0 \qquad \text{vs.} \qquad H_A : \delta_i \neq \delta \text{ for all } i, \text{ or } \alpha < 0. \tag{5.12}$$

Thus, convergence also holds for $\alpha = 0$, which is ensured via the slowly increasing function $L(t)$. According to Phillips and Sul (2009), this allows us to empirically capture cases of slow transition and slow convergence. In turn, the alternative hypothesis H_A points to divergence, but also considers the possibility of club convergence. This feature is used in the clustering algorithms in Sections 5.3.3 and 5.3.4.

To test H_0 against H_A, Phillips and Sul (2007) developed the following procedure.

1. Step 1: Calculate the cross-sectional variance ratio H_1/H_t.

2. Step 2: Estimate the following regression using OLS:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \hat{a} + \hat{b}\log t + \hat{u}_t, \tag{5.13}$$

   for $t = [rT], [rT]+1, \ldots, T$ for some $r > 0$.

3. Step 3: Given $\hat{b} = 2\hat{a}$, perform a one-sided t test for $\alpha \geq 0$ using heteroskedasticity and autocorrelation consistent (HAC) standard errors. H_0 is rejected if the corresponding $t_{\hat{b}}$ is below the critical value (-1.65 at the 5% significance level).

In Equation (5.13), the term $-2\log(\log t)$ acts as a penalty function that improves the discriminatory power of the log t test, in particular in the boundary case of $\alpha = 0$. Moreover, the first r observations are truncated to attach more weight to the more recent data points. Monte Carlo simulations suggest the use of $r = 0.3$ and $L(t) = \log t$ for panel sizes up to $T = 50$ (Phillips and Sul, 2007).

5.3.3 The PS Club Clustering Algorithm

It was argued that the alternative hypothesis H_A also comprises the possibility of club convergence. To detect convergence clubs in a given panel, Phillips and Sul (2007) proposed the following clustering algorithm.

1. Last observation ordering: Sort the panel units i in descending order according to the size of the last observation.

2. Core group formation: Conduct a log t test for the first two units of the (remaining) panel. If H_0 cannot be rejected, add the next subsequent unit and conduct a log t test. Continue adding units until H_0 is rejected. The core group contains the first n units ($n \geq 2$) for which H_0 cannot be rejected. If H_0 is rejected for the first two units, drop the first unit from the current core-group formation loop and proceed with the next two units. If H_0 is rejected for all pairs of units, the whole (remaining) panel diverges and the algorithm stops.

3. Club formation: Perform log t tests on the core group with each single remaining unit and record the $t_{\hat{b}}$ data. Perform a log t test on the core group together with all units for which $t_{\hat{b}}$ is greater than a certain critical value c. If H_0 cannot be rejected, these units constitute a convergence club. If H_0 is rejected, increase the critical value c and repeat the last step.

4. Stopping rule: If one unit is left in the remaining panel, this unit diverges. Otherwise, perform a log t test for all remaining units. If H_0 cannot be rejected, the remaining panel converges and constitutes another convergence club. If H_0 is rejected, repeat the algorithm from the second step onwards. If no unit is left, the algorithm stops.

A higher critical value c increases the discriminatory power of the log t test, thereby increasing the probability that the algorithm will detect more clubs. Phillips and Sul (2009) suggested pairwise log t tests for adjacent clubs to consolidate the number of clubs. Lyncker and Thoennessen (2017) generalized this idea and proposed a club merging algorithm that chooses the most reasonable club merger first to prevent inferior club consolidation. This is of particular interest if many clubs are initially detected (e.g., because of a high c value) and multiple club mergers are possible. Lyncker and Thoennessen (2017) also proposed an algorithm that checks whether diverging regions can be merged with the consolidated clubs.

Phillips and Sul (2007) suggested that the critical value be set to $c = 0$. However, in a Monte Carlo study, Lyncker (2016) showed that the clustering results considerably improve for high c (e.g., $c = 100$) if the PS algorithm is combined with a club merging algorithm similar to the one proposed by Lyncker and Thoennessen (2017).

In this respect, Lyncker (2016) also highlighted some minor drawbacks of the PS algorithm. The step for last observation ordering and the hierarchical procedure for core group formation implicitly assume that the order of the last observations comes closest to the actual order if $t \to \infty$. Although this probably holds true in many cases, the size of the last observations might well be the result of pronounced transitional heterogeneity for some units. Thus, the procedures in the first two steps of the PS algorithm predetermine club identification, which might not be appropriate in all cases. A related critique refers to the pairwise log t tests for core group formation. For a given set of subsequently ordered units, it could well be the case that all pairwise log t tests reject H_0 even if some of these units actually form a convergence club. Finally, case-by-case adjustment of the critical value c in the third step might create clubs with different conservative clustering.

5.3.4 Alternative Club Clustering Algorithm

On the basis of critiques of the PS algorithm, Lyncker (2016) proposed the following algorithm.

1. Log t test matrix: Create a matrix with all possible pairwise log t tests for all (remaining) units.

2. Merging rule: Identify the highest $t_{\hat{b}}$ within the log t test matrix. If H_0 cannot be rejected for the corresponding units, merge both units to form a club. If H_0 is rejected, the algorithm stops and all remaining units are clubs or diverging regions.

3. Loop or end: Treat the club found in the second step as a single unit. If only one unit is left, the whole panel converges and the algorithm stops. Otherwise, repeat the algorithm from the first step onwards.

This hierarchical cluster (HC) algorithm detects clubs in a more general way than the PS algorithm and thereby circumvents the minor drawbacks of the PS procedure as outlined in Section 5.3.3. In addition, it does not use the information obtained during ordering of the last observations. Monte Carlo simulations revealed that the appropriateness or superiority of each algorithm depends on various factors, in particular the panel length and width and the convergence speed assumed (Lyncker, 2016). Section 5.4 compares and discusses results for the EPS and the HC algorithm.

5.3.5 Club Core Identification

Lyncker and Thoennessen (2017) pointed out that clustering based on the PS log t test might lack stability with respect to size and the parameter estimates and their statistical significance. For example, inclusion of an additional region in an existing club might be justified via the log t test even if this substantially changes the estimated convergence speed. As a consequence, the estimated convergence speed holds for the cluster of units, but this coefficient estimate might not be representative for the club if it is biased by inclusion of transition regions. For this and other reasons, identification of a statistically stable core group of units in an existing club is of empirical interest. On the basis of the HC algorithm in Section 5.3.4, we propose the following procedure to identify the core group of units within a club.

1. Maximum number of clubs: Perform the HC algorithm for a set of increasing t values. Choose the highest t value that identifies to the largest number of clubs (t^{min}).

2. Core identification: For each club identified by t^{min}, perform the HC algorithm for a set of increasing t values. Choose the highest t value that still leads to a cluster within the club (t^{max}). The corresponding units constitute the club core. The remaining club units are transition units.

3. Speed stability: For each club, take the n club core units, perform n log t tests by dismissing one unit at a time, and record the corresponding convergence speeds. Calculate the standard deviation and the range for all convergence speeds.

4. Extended core: For each club, build subgroups consisting of the club core and each transition unit at a time. For each subgroup, perform the speed stability procedure of Step 3. Choose the subgroup for which the speed stability procedure leads to the smallest sum of the standard deviation and range. If this sum is smaller than the sum for the core group, and if the corresponding $t_{\hat{b}}$ is larger than t^{min}, the subgroup constitutes the new core group. Repeat Step 4 until no further transition unit can be added to the core group.

Identification of the club core in Step 2 requires that the club being considered does not contain any non-club units, otherwise more than one club core could be identified. Therefore, Step 1 detects the maximum number of clubs within the whole panel. For this purpose, the HC algorithm is performed for a set of different t values (e.g., $t \in [-1 : 0.5 : 20]$) such that different conservative club clusters are obtained. In most cases, the number of clubs will first increase with t. However, from a certain t value onwards, the conservativeness of the clustering becomes too strong such that fewer clubs and ultimately only diverging regions are detected.

Having found t^{min} leading to the largest number of clubs, Step 2 examines each club at a time to determine t^{max}, the most conservative t value that still leads to a cluster of at least two units. This cluster constitutes the club core. The core is usually statistically stable (high $t_{\hat{b}}$ from the log t test) and exhibits a fast convergence speed. It should be noted that all clubs are clustered according to t^{min}, but the corresponding club cores might be based on different t^{max} values.

Steps 3 and 4 are optional refinements of the preceding steps. In Step 3, the club core from Step 2 is set as the reference point for subsequent modifications. If the merger of the club core with certain transition regions increases the stability of the club core convergence speed, the club core is augmented stepwise with these transition regions. The stability of the convergence speed for a certain group is indirectly determined by dismissing one unit at a time and recording the convergence speed. The extended core group is preferred over the reference core group if the sum of the standard deviation and range for the convergence speeds is smaller than the reference sum, and if the corresponding t value is greater than t^{min}.

The power of Steps 1 and 2 lies in the nondiscretionary determination of the core group. No values have to be set, not even a significance level. By contrast, extension of the club core in Step 4 is based on at least three discrete decisions. First, the log t test criterion (i.e., clustering according to the highest t value) is partly dismissed in favor of a convergence speed criterion. Hence, clustering conservativeness is loosened to strengthen the stability of the convergence speed. Second, the convergence speed criterion refers to the sum of the standard deviation and range for the convergence speed of different subgroups. This choice is also discrete in nature and could be replaced by other criteria. Third, the principle whereby the core group is only be extended if — besides the speed criterion — the corresponding t value is greater than t^{min} is discrete. Hence, decisions on whether or not to extend the club core (Steps 3 and 4) and how to set the discrete values depend on the research question and are ultimately chosen by the researcher.

5.3.6 Stability of Core Speed and Core Composition

Based on the CCI results, the empirical sections examine the stability of the club cores identified. To test whether the convergence speeds of the club cores detected are stable across time, the log t test is performed on each core for rolling windows of 20 years length in Section 5.4.4. The resulting time series for convergence speeds have a length of 13 observations. Regression analysis is performed on these time series to assess the overall trend for convergence speeds. To this end, OLS techniques with HAC standard errors are used to account for potentially strong serial correlation in the data generated.

In Section 5.4.5, the rolling window for observation is shortened to 4 years, which generates time series of length $T = 29$. Although this procedure is not suitable for any reliable inference regarding the height of the convergence speed, it allows us to test for structural breaks in the development of the convergence speed. Structural breaks are endogenously identified as proposed by Andrews (1993) and Bai and Perron (2003). On the basis of the results, an unrestricted model with the most pronounced structural breaks is estimated to identify overall trends in the convergence speed.

The stability of the club cores with respect to size and composition is tested in Section 5.4.6. For this purpose, a new panel containing all core regions is compiled. Step 1 of the CCI procedure is then performed for a rolling window of 20 years. This reveals the total number of club cores and the club core affiliation for each region for a series of 13 years.

5.3.7 Data

Data are taken from the European Regional Database elaborated by Cambridge Econometrics. The variable of interest is income per capita, which is obtained by dividing the regional gross value added in 2005 prices by the total population of the region. The largest panel has a length of 32 observations per unit and covers the years 1980–2011. It consists of 68 NUTS-1 regions of the EU-15 (i.e., all EU member countries as of 2003). This panel is split into two subpanels: one comprising NUTS-1 regions from the first 12 eurozone countries, and the other containing the non-eurozone countries of the EU-15 (i.e. the UK, Denmark, and Sweden).

Table 5.1 summarizes key statistics for all countries and all country groups. A few points are worth mentioning. First, the number of regions and hence observations (regions $\times$ panel length T) does not necessarily depend on the country size. For example, the five and nine NUTS-1 regions for Italy and France, respectively, are not proportional to the population of these countries because NUTS-1 regions are based on administrative units. Since no appropriate data based on functional units are available for this length, our investigation in this study is based on NUTS-1 data. A second point apparent from Table 5.1 is that the increase in mean income per capita between 1980 and 2011 differs greatly among countries. For instance, income in 1980 in both Austria and Italy was close to the EU-15 average. By 2011, income had increased by 73% in Austria but only by 22% in Italy. Distinct country-specific differences can also be identified with respect to the coefficient of variation (CV). For example, Portugal and Sweden had a similar CV in 2011. However, from 1980 onwards the Portuguese CV decreased by 44%, whereas the Swedish CV increased by 127%. Finally, the non-eurozone group (Denmark, Sweden, UK) clearly outperformed the eurozone-12 group with respect to income growth between 1980 and 2011. For all three panels, CV slightly increased, which might be a first indication of diverging forces across NUTS-1 regions in Western Europe.

Table 5.1: Overview of Sample of EU-15 regions, 1980-2011.

country	Eurozone	no. of obs.	no. of regions	mean inc. 1980	mean inc. 2011	CV 1980	CV 2011
Austria	YES	96	3	16.388	28.290	0.099	0.107
Belgium	YES	96	3	22.717	32.408	0.614	0.498
Germany	YES	320	10	23.663	29.455	0.223	0.223
Denmark	NO	32	1	21.101	32.000	0.000	0.000
Spain	YES	224	7	11.653	18.463	0.190	0.205
Finland	YES	64	2	14.898	33.537	0.034	0.274
France	YES	288	9	16.074	23.123	0.225	0.281
Greece	YES	128	4	10.355	13.634	0.034	0.280
Ireland	YES	32	1	26.009	32.389	0.000	0.000
Italy	YES	160	5	16.718	20.421	0.308	0.271
Luxemburg	YES	32	1	25.938	57.287	0.000	0.000
Netherlands	YES	128	4	18.004	28.942	0.110	0.094
Portugal	YES	96	3	11.807	13.798	0.366	0.203
Sweden	NO	96	3	17.766	30.362	0.080	0.181
United Kingdom	NO	384	12	13.668	25.795	0.233	0.288
EU-15	-	2176	68	16.659	25.253	0.353	0.358
Euro-12	-	1664	52	17.199	24.703	0.369	0.387
non-Euro-12	-	512	16	14.901	27.039	0.242	0.261

Notes: Mean income per capita measured in 1000 Euro. CV denotes the coefficient of variation of income per capita.

5.4 Results

5.4.1 Club Clustering

Our empirical analysis starts with a club clustering based on the PS log t test. To this end, both the EPS algorithm and the HC algorithm proposed by Lyncker (2016) are used. As already mentioned, the EPS algorithm combines the PS (2007) clustering algorithm and the formalized club merging algorithm as proposed by Lyncker (2016).

In a Monte Carlo study, Lyncker (2016) showed that the cluster results of the PS procedure considerably improve for high critical values in many cases. For a panel of length $T = 30$ and width $N = 50$ ($T = 30$,$N = 100$), a critical value of $c = 100$ ($c = 5$) is recommended to achieve the best club assignment of regions and the best detection rate for the total number of clubs. Hence, the PS procedure is also performed with $c = 100$. Lyncker (2016) also compared the performance of the PS algorithm and the HC algorithm. For the given panel length and width, the PS algorithm is preferable for optimizing correct assignment

Table 5.2: EU-15 panel: results of different clustering procedures.

method	crit. t-value	club	club size	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg. inc. 1980	avg. inc. 2011	no. div. reg.
log t	-1.65	1	68	-0.600 (0.058)	-10.287	-0.300	16.659	25.253	-
PS	-1.65	1	5	0.450 (0.140)	3.216	0.225	25.877	45.640	0
(c=0)		2	43	0.150 (0.115)	1.304	0.075	17.253	26.760	
		3	18	-0.079 (0.100)	-0.788	-0.039	13.108	17.550	
		4	2	-0.321 (1.844)	-0.174	-0.160	12.781	11.206	
PS	-1.65	1	3	0.748 (0.174)	4.302	0.374	29.375	51.921	0
(c=100)		2	18	0.346 (0.089)	3.894	0.173	20.827	32.621	
		3	34	0.547 (0.059)	9.296	0.273	15.506	23.251	
		4	13	-0.323 (0.199)	-1.624	-0.162	10.968	14.129	
HC	-1.65	1	9	0.193 (0.128)	1.506	0.096	26.707	42.631	0
		2	47	-0.029 (0.054)	-0.534	-0.014	16.199	24.821	
		3	12	-0.187 (0.203)	-0.921	-0.093	10.922	13.907	
HC	2	1	8	0.729 (0.143)	5.089	0.365	26.803	40.800	2
	(=t^{min})	2	4	1.215 (0.101)	12.036	0.607	20.137	31.567	
		3	25	0.276 (0.047)	5.813	0.138	17.208	26.316	
		4	18	0.799 (0.211)	3.789	0.400	13.923	21.247	
		5	9	0.652 (0.187)	3.493	0.326	10.618	14.826	
		6	2	2.333 (1.048)	2.226	1.166	12.611	11.306	

Notes: PS: PS (2007) clustering algorithm with club merging algorithm as proposed in Lyncker and Thoennessen (2015). c: critical value to be set in the PS procedure. HC: hierarchical clustering as proposed in Lyncker (2016).

of regions to specific clubs, but the HC algorithm is more reliable in detecting the correct number of clubs. When both criteria are considered, both algorithms should perform equally well.

Table 5.2 presents the main results of the clustering procedures for the EU-15 panel. Overall convergence is rejected by a clearly negative $t_{\hat{b}}$ of -10.287. The PS algorithm with $c = 0$ (Phillips and Sul, 2009, as recommended by) detects four convergence clubs. However, only the first club is significantly different from zero, so Clubs 1–3 are weak convergence clubs (Phillips and Sul, 2009). With $c = 100$, four clubs are also detected, but this time only Club 4 is statistically non-significant. The HC algorithm detects three convergence clubs, but all of them are weak according to the $t_{\hat{b}}$ values. None of these three settings identifies diverging regions. (Results for the second run of the HC algorithm are discussed in Section 5.4.2).

According to the results for the HC algorithm, which should perform better in correct detection of the number of clubs, it is most likely that there are three convergence clubs among NUTS-1 regions. Nevertheless, the PS procedure with $c = 100$, which detects four clubs, seems more appropriate in this case, since the $\hat{b}$ coefficients for Clubs 1–3 are statistically very stable.

Tables 5.8 and 5.9 in the Appendix provide cluster results for the two subpanels. In the case of the eurozone panel, the PS algorithm with $c = 100$ and the HC algorithm detect the same number of clubs as found in the EU-15 panel; however, both procedures largely do not deliver statistically reliable $\hat{b}$ coefficients. This problem also occurs for clustering in the non-eurozone panel, for which different settings and algorithms consistently detect two convergence clubs.

5.4.2 Club Core Identification

The previous section revealed weaknesses for the PS and HC algorithms: in both procedures, a certain clustering might be statistically justified by the significance level chosen (e.g., $t = -1.65$ at the 5% level) but the resulting convergence clubs might be 'weak' in the sense that their $\hat{b}$ coefficients are not significantly different from zero. Thus, it is hard to draw any inferences regarding the convergence speed, so more precise clustering is required.

According to Step 1 of the CCI procedure in Section 5.3.5, the maximum number of clubs is identified via the HC algorithm for different critical t values. Table 5.3 lists results for the EU-15 panel. For $t = -2$ and $t = -1$, the HC algorithm finds the three clubs detected for $t = -1.65$ in Table 5.2. The highest t value that still delivers a cluster of regions is $t = 15$. The t value that identifies the highest number of clubs lies between these two values at $t^{min} = 2$. For this case, a maximum of six clubs are detected. The results in Table 5.2 reveal that the $\hat{b}$ coefficients for all six clubs are significantly different from zero.

Table 5.3 also reveals how these six clubs partly amalgamate for lower t values. For $t = 1$, Club 2 merges with Club 3, and is joined by Club 4 at $t = -1$. By contrast, for lower t values, Club 1 only gains one additional region, which is classified as diverging at $t = 2$. It is worth noting how addition of this single region completely changes the speed parameter $\hat{\alpha}$ of Club 1, from which the weakness of less conservative clustering becomes apparent.

To identify the most conservative core for each club, Step 2 of the CCI procedure increases the critical t value for each club up to the point at which clustering is barely detected. The corresponding cluster constitutes the core of the club in the sense that the core contains regions whose growth path developed very similar according to the log t test. For each club, this core might be achieved at very different t values, t^{max}. Table 5.3 shows that the core for Club 3 is achieved at $t^{max} = 15$; compared to the club cluster at $t^{min} = 2$, 13 out of originally 25 regions belong to the core of Club 3. By contrast, increasing the t-value from $t^{min} = 2$ onwards does lead to the dissolution of Club 6; in this case it holds that $t^{min} = t^{max}$. The development of Club 2 illustrates another possible feature of this

Table 5.3: EU-15 panel: club sizes and convergence speeds ($\hat{\alpha}$) for different t-values .

crit t-value	no. of clubs	no. of div. reg.	Club 1 size ($\hat{\alpha_1}$)	Club 2 size ($\hat{\alpha_2}$)	Club 3 size ($\hat{\alpha_3}$)	Club 4 size ($\hat{\alpha_4}$)	Club 5 size ($\hat{\alpha_5}$)	Club 6 size ($\hat{\alpha_6}$)
-2	3	0	9 (0.096)		47 (-0.014)		12 (-0.093)	
-1	3	0	9 (0.096)		47 (-0.014)		12 (-0.093)	
0	5	0	9 (0.096)		29 (0.061)	18 (0.400)	9 (0.326)	3 (0.761)
1	5	0	9 (0.096)		29 (0.061)	18 (0.400)	9 (0.326)	3 (0.761)
2	6	2	8 (0.365)	4 (0.607)	25 (0.138)	18 (0.400)	9 (0.326)	2 (1.166)
3	5	4	8 (0.365)	4 (0.607)	25 (0.138)	18 (0.400)	9 (0.326)	
4	5	6	8 (0.365)	4 (0.607)	25 (0.138)	17 (0.591)	8 (0.296)	
5	5	6	8 (0.365)	4 (0.607)	25 (0.138)	17 (0.591)	8 (0.296)	
6	5	11	7 (0.350)	4 (0.607)	24 (0.193)	16 (0.403)	6 (0.598)	
7	4	19		4 (0.607)	23 (0.212)	16 (0.403)	6 (0.598)	
8	3	23			23 (0.212)	16 (0.403)	6 (0.598)	
9	3	23			23 (0.212)	16 (0.403)	6 (0.598)	
10	2	31			22 (0.198)	15 (0.529)		
11	1	46			22 (0.198)			
12	1	48			20 (0.310)			
13	1	48			20 (0.310)			
14	1	49			19 (0.252)			
15	1	55			13 (0.364)			
16	1	68						

Notes: Results based on a hierarchical clustering (cp. Section 5.3.4) of the EU-15 panel.Critical t-value increased in steps of 0.5 (Table depicts integer t-values only). t^{min} identified at 2.0.

proceeding; the increase of the t-value does not decrease the Club size, so the club core is already clustered at t^{min}.

Analogous CCI results for the eurozone and non-eurozone panels are provided in the Appendix (cp. Table 5.11 and Table 5.12). The eurozone panel contains a maximum of five convergence clubs identified at $t^{min} = 6.5$. In this context, a further possible feature of the method becomes apparent: not all possible clubs have to appear at the same t value. A sixth club emerges for $0 \leq t \leq 2$ and contains regions classified as diverging for $t^{min} = 6.5$. However, although five clubs are already detected at $t = 2$, this value is not the correct t^{min}, since Club 1 still contains the core regions of Club 2. Therefore, Step 1 of the CCI procedure sets t^{min} to the highest t value that leads to the largest number of clubs. Finally, the maximum number of clubs detected in the non-eurozone panel is two.

Figure 5.3 shows the club core clustering for the EU-15 panel. (An overview of all NUTS-1 regions with the club and core classifications for all three panels is listed in Table 5.6.) Club cores that amalgamate at $t = -1.65$ are depicted in the same color with similar color strength. Transition regions among different clubs are colored in light blue, and diverging regions in dark blue.

The core regions of the highest-income club (Club 1) are spread over the map and comprise hotspots such as London, Brussels, and Hamburg. At the other extreme, southern

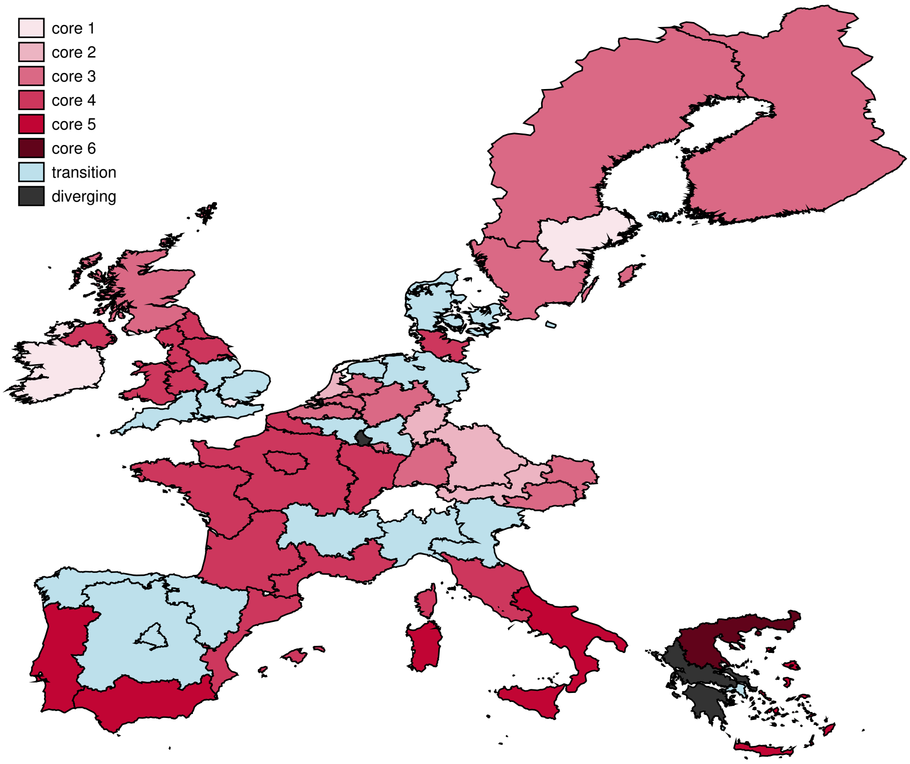

Fig. 5.1: EU-15 panel: club clustering (1980–2011).

European regions in the GIPS countries (Greece, Italy, Portugal, Spain) are core regions of the low-income clubs (Clubs 5 and 6). Most regions of France, Germany, Finland, and Sweden, as well as middle-England, Scotland, Wales, and Northern Ireland, belong to the core of one of the three middle-income clubs (Clubs 2–4). The higher-income clusters of southern Germany, Austria, and the Netherlands stand out. Regions in Spain, northern Italy, northern Germany, Denmark, and the south of England are in transition. Section 5.4.5 provides a more detailed analysis of the club and core clusters detected.

5.4.3 Extended Club Core Identification

The CCI procedure in Section 5.3.5 includes two further steps that are of interest if the research question focuses on actual convergence speed in a club. So far, two different convergence speeds were recorded, both of which might not represent the actual convergence speed of a club. The speed detected after Step 1 of the CCI procedure might be biased by transition regions that have not been excluded so far. In addition, the club core speed after Step 2 measures only the speed of the inner core, which might not be representative of the whole club. Steps 3 and 4 of the CCI procedure add to the club core the transition regions that stabilize the parameter estimates according to certain criteria.

Table 5.4: EU-15 panel: stabilising club core 5.

	Club 5	club core	ext. core	ext. core
regions	$\hat{\alpha}$s	$\hat{\alpha}$s	$\hat{\alpha}$s	$\hat{\alpha}$s
pt3	0.296	-	-	-
es7	0.382	-	0.598	0.412
es4	0.357	-	-	0.380
fr9	0.250	0.533	0.312	0.214
itg	0.273	0.491	0.319	0.235
es6	0.293	0.536	0.299	0.224
itf	0.315	0.552	0.360	0.280
gr4	0.338	0.695	0.396	0.302
pt1	0.509	1.305	0.510	0.424
std. of speeds	0.077	0.311	0.114	0.086
range of speeds	0.259	0.814	0.299	0.209
std. + range	0.336	1.125	0.413	0.295
speed	0.326	0.598	0.380	0.296
log t test	3.493	9.417	5.978	6.636

Notes: Upper part of table: group convergence speeds if the respective region is dismissed from the group. Middle part of table: standard deviation and range of these speeds. Lower part of table: log t test and convergence speed of whole group.

Table 5.4.3 illustrates the procedure for Club 5 of the EU-15 panel. The club contains nine regions, three of which are identified as transition regions. Temporary removal of these three regions increases the value for the log t test from $t = 3.493$ to $t = 9.417$ and increases the convergence speed from $\hat{\alpha} = 0.326$ to $\hat{\alpha} = 0.598$. Again, the speed of the club core is correct for the core itself, but might not be representative of the whole club (notwithstanding the fact that the club core is the most significant part of the club from a statistical perspective).

To perform Steps 3 and 4 of the core identification procedure, Table 5.4.3 lists a convergence speed for each region, calculated by excluding the region from its corresponding group. The standard deviation and range for the convergence speed are also listed. Step 4 checks whether addition of another region decreases the sum of the standard deviation and range, under the condition that the log t test for this extended core group still exceeds a certain threshold (t^{min}). If applicable, the region that yields the greatest decrease is added to the core group. In our case, this holds for region es7, for which the sum decreases from 1.125 to 0.413 and the log t test for the whole group is greater than t^{min}. (Results for the other two regions are not shown.) In the next step, region es4 is also added to the core group, thereby further decreasing the sum of the standard deviation and range. According to the decision criteria, inclusion of pt3 is not justified (compare columns two and five of Table 5.4.3.) From a real world perspective, this result seems reasonable, since pt3 is the Portuguese overseas region of Madeira. Hence, it can be concluded that Club 5 most probably converges around a speed of $\hat{\alpha} = 0.296$.

Table 5.5: All panels: stabilized convergence speeds.

panel	ext. core 1	ext. core 2	ext. core 3	ext. Core 4	ext. core 5	ext. core 6
EU-15						
former club speed	0.365	0.607	0.138	0.400	0.326	1.166
core speed	0.350	0.607	0.364	0.529	0.598	1.166
ext. core speed	0.365	0.607	0.173	0.529	0.296	1.166
ext core log t test	5.089	12.036	5.468	10.221	6.636	2.226
ext. core size	8	4	23	15	8	2
Eurozone						
former club speed	0.504	0.607	0.148	0.242	0.598	
core speed	0.504	0.607	0.371	0.254	0.598	
ext. core speed	0.533	0.607	0.445	0.254	0.598	
ext. core log t test	6.336	12.036	7.767	6.455	9.417	
ext. core size	6	4	13	7	6	
non-Eurozone						
former club speed	0.714	0.377				
core speed	0.714	0.377				
ext. core speed	0.714	0.377				
ext. core log t test	8.579	9.947				
ext. core size	3	4				

Results for all three panels are provided in Table 5.5. It is evident that Steps 2–4 of the CCI procedure do not always lead to different results; for example, the core and the extended core of Club 2 in the EU-15 panel are identical to the club itself; hence, the convergence speeds also remain unchanged. In other cases, all three convergence speeds differ, such as for Club 3 in the eurozone panel.

When interpreting the results, the very low number of regions in some groups should be kept in mind. For instance, the very high convergence speeds for Club 6 ($\hat{\alpha} > 1$) in the EU-15 panel can be explained by the crossing of relative transition paths of the two regions in the club; for this case, a deeper interpretation would be useless. Besides such extreme cases, the convergence speeds for the extended cores are all very high compared to the 2% reported in much of the empirical literature (Abreu et al., 2005). This can be explained by the fact that the log t test is a test for club convergence, and the possible algorithms explicitly cluster regions that are already very similar. This effect is strengthened by very conservative clustering, as implied by the CCI procedure. Finally, the fact that this study investigates relatively small panels (N = 68, 52 and 16) might lead to the detection of comparatively small, homogeneous clubs with a rapid club convergence speed.

5.4.4 Stability of Convergence Speed

Having identified the maximum number of clubs and their (extended) cores, we now investigate the development of convergence speeds over time. To achieve the highest possible statistical reliability, we focus on the (very conservatively estimated) club cores identified in Section 5.4.2 and on pooled groups of regions (i.e., all cores, all transition regions, and the whole panel).

For each club core or group of regions, we perform moving log t tests to estimate $\hat{\alpha}$ values based on observations over 20 years. The first log t test covers the period 1980–1999 and the last one the period 1992–2011, resulting in a time series of 13 $\hat{\alpha}$ values for each club core. OLS regression analysis is conducted for these time series. HAC standard errors are applied to control for heteroskedasticity and autocorrelation of the residuals.

Table 5.6: Euro-15 panel: development of the convergence speed.

	core1	core2	core3	core4	core5	cores	trans.	all
# reg.	7	4	13	15	6	47	19	68
year	$\hat{\alpha_1}$	$\hat{\alpha_2}$	$\hat{\alpha_3}$	$\hat{\alpha_4}$	$\hat{\alpha_5}$	$\alpha_{\hat{cores}}$	$\alpha_{\hat{trans}}$	$\alpha_{\hat{all}}$
1999	-0.113	0.167	0.285	0.304	0.819	-0.404	-0.490	-0.453
2000	-0.045	0.218	0.269	0.322	0.760	-0.419	-0.467	-0.455
2001	0.025	0.242	0.262	0.351	0.667	-0.417	-0.435	-0.443
2002	0.089	0.256	0.223	0.375	0.578	-0.404	-0.360	-0.414
2003	0.125	0.244	0.172	0.378	0.458	-0.381	-0.270	-0.375
2004	0.163	0.179	0.105	0.313	0.419	-0.367	-0.207	-0.348
2005	0.178	0.178	0.077	0.219	0.348	-0.351	-0.147	-0.324
2006	0.187	0.196	0.026	0.113	0.243	-0.339	-0.084	-0.304
2007	0.171	0.209	-0.024	0.028	0.112	-0.331	-0.042	-0.294
2008	0.121	0.213	-0.050	0.012	-0.014	-0.327	-0.021	-0.291
2009	0.061	0.180	-0.069	-0.005	-0.117	-0.341	-0.044	-0.306
2010	-0.003	0.141	-0.088	-0.033	-0.132	-0.363	-0.098	-0.332
2011	-0.065	0.166	-0.115	-0.077	-0.187	-0.394	-0.166	-0.368
model								
const.	-.231***	0.194***	0.361***	0.364***	0.929***	-0.460***	-0.672***	-0.536***
t	0.112***	0.010	-0.044***	-0.001	-0.089***	0.025**	0.113***	0.047***
t^2	-0.008***	-0.001	0.000	-0.003	0.000	-0.001**	-0.005***	-0.002***
R squ.	0.990	0.409	0.981	0.892	0.991	0.717	0.933	0.890

Notes: Convergence speeds $\hat{\alpha}$ are based on a moving log t test over 20 years. The first observation lies in 1999 for the years 1980–1999. M0: $speed_t = const. + \gamma_1 \cdot trend + \gamma_2 \cdot trend^2 + \epsilon_t$. Regressions based on OLS with HAC-standard errors (Bartlett-Kernel with Newey-West fixed bandwidth). 'core 6' (2 reg.) not reported. ***p<0.01, **p<0.05, *p<0.1.

Table 5.4.4 summarizes the estimated convergence speeds and regression results for the EU-15 panel (a graphical illustration is provided in Figure 5.3 in the Appendix). The constant term is highly significant in all eight cases. It is evident that club convergence occurs for cores 2–5 between the 1980 and 1999 (cp. results for the year 1999). By contrast, this does not hold for core 1 and the different pooled groups. Convergence speeds for cores 3 and 5 exhibit a downward trend that is significant at the 1% level. The trend coefficients for cores 2 and 4 are not significant. The speeds for core 1 and the pooled groups exhibit a concave trend; the positive trend coefficient and the negative squared trend coefficient are significant at 5% or better. As expected, the convergence speed for the pooled groups develops in a smoother manner. Nevertheless, both trend coefficients are substantially greater for the group of transition regions, whereas the development is very similar for all the core units and the whole panel.

5.4.5 Trends and Structural Break in Convergence Speed

The previous section showed that the development of the club convergence speed among European NUTS-1 regions was unstable within groups and cores, as well as differing among them. Overall, the data point to a downward trend for club convergence speeds, at least for the last years under consideration. However, the short length of the time series and the smooth nature of the data (as a result of the moving log t test over 20-year windows) mean that inferences besides the one described in Section 5.4.4 are not feasible.

Therefore, we shortened the moving average window for the log t test to 4 years. The resulting time series for each group now spans 29 years, from 1983 to 2011. This shorter window has less of a smoothing effect on the speed values, so the timing of potential trend changes can be investigated. However, the absolute height of single speed values is not suitable for any further inference, since these data are based on only 4 years of observations.

Similar to Section 5.4.4, the time series for each core group and each pooled group are examined using OLS regression with HAC standard errors. The results are presented in Tables 5.13, 5.14, and 5.15 in the Appendix. In the baseline model ($M0$), the convergence speed is explained by a constant and a time trend. In addition, two restricted models were estimated: $M1$ includes one structural break (in intercept and trend) and $M2$ models two structural breaks. The structural break in $M1$ is detected using the Quandt–Andrews endogenous break test (Quandt, 1960; Andrews, 1993), whereas the two breaks in $M2$ are based on a Bai–Perron multiple-break test (Bai and Perron, 2003). Finally, Wald tests are conducted to find the model that best describes the development of the convergence speeds.

Tables 5.13, 5.14, and 5.15 reveal that results across club cores and other groups exhibit substantial differences in regression coefficients and the corresponding significance. However, all club cores and groups experience at least one significant structural break throughout the period. Across all units, break points are most often identified in or around the years 1991, 1997, and 2003.

Therefore, a third restricted model that exogenously sets these specific break dates is estimated ($M3$). The main results are reported in Table 5.4.5. Owing to the relatively short time series ($\# = 29$) and the comparatively high number of structural breaks ($\# = 3$), the results for $M3$ should be interpreted with caution. Nevertheless, the following main

Table 5.7: EU-15 panel: trends and structural breaks in convergence speeds.

group	core 1	core 2	core 3	core 4	core 5	cores	trans	all
EU								
#reg.	7	4	13	15	6	47	19	52
t	0.011	-0.035***	-0.017**	-0.029**	0.105***	-0.008*	-0.006	-0.009**
D1t	0.007	0.042***	0.022**	0.081*	-0.135***	0.002	0.010	0.011**
D2t	-0.044***	-0.030***	-0.021***	-0.087*	-0.014	0.009***	-0.003	-0.001
D3t	0.012*	-0.002	0.004	0.015	0.097***	-0.016***	-0.027***	-0.016***
Wald	25.4***	41.2***	12.8***	5.8***	24.7***	30.6***	51.2***	79.3***
EZ								
#reg.	6	4	9	7	6	32	7	52
t	-0.032**	-0.035***	-0.017	0.004	0.105***	-0.001	0.000	-0.007*
D1t	0.056***	0.042***	0.021	-0.014	-0.135***	-0.004	-0.048***	0.011**
D2t	-0.043***	-0.030***	-0.029***	0.039***	-0.014	0.009***	0.004	-0.003
D3t	0.001	-0.002	0.007	-0.059***	0.097***	-0.020***	0.048	-0.017***
Wald	23.2***	41.2***	15.0***	24.9***	24.7***	13.7***	25.3***	85.7***
nEZ								
#reg.	3		4			7		16
t	0.011		-0.102***			-0.007		-0.008
D1t	0.030		0.068**			0.040*		0.013
D2t	-0.033		-0.033***			-0.055*		0.003
D3t	-0.058***		0.061***			-0.002		-0.021*
Wald	11.9***		30.3***			8.1***		2.4*

Notes: Baseline regression M0: $speed_t = const. + \gamma \cdot trend + \epsilon_t$. M3: structural breaks (intercept and slope) in 1991, 1997, and 2003. Regressions based on OLS with HAC-standard errors (Bartlett-Kernel with Newey-West fixed bandwidth). 'Wald' reports F-statistics based on a test of M3 v M0. Only slope coefficients reported. 'core 6' (2 reg.) of the EU-15 not reported. ***p<0.01, **p<0.05, *p<0.1. Tests performed with Stata12.

trends can be extracted. (Owing to strong similarities to the eurozone panel, results for the EU-15 panel are not discussed.)

- Overall convergence: Since 2003, the overall convergence speed in all eurozone regions and in the group of core regions has been decreasing, and the convergence speed for the group of transition regions has been stable (not significant).

- Club convergence: Since 1997, the convergence speed in high-income club cores of the eurozone has been decreasing. Since 2003, the convergence speed in the low-income club core of the eurozone has been increasing. Results for the medium-income club cores are mixed.

- Non-eurozone panel: Overall, the convergence speed in all non-eurozone regions has developed in a similar manner to the eurozone panel (although less significant). Since 2003, the convergence speed in the high-income club of the non-eurozone panel has been decreasing; 1991 and 1997 are not significant break dates, as in the high-income club of the eurozone panel. Since 2003, the convergence speed in the medium-income club core has become stable.

The break years set in regression $M3$ are the break points identified in the data. Since the data are based on a moving average of 4 years, the actual breaks can be located up to 3 years before the data break point. Keeping this in mind, a few decisive political and economic events might be related to these trend changes: the 1986 Single European Act, Black Wednesday in 1992, the 1992 Maastricht Treaty, introduction of the euro in 1999, and bursting of the dot-com bubble in 2000. Nonetheless, since the moving average nature of the convergence speed time series does not allow detection of an exact break date, drawing any conclusions would be speculative. Since a more detailed assessment of potential relationships is beyond the scope of our study, this topic is left for further research.

5.4.6 Club Core Stability

The results in the previous two sections raise the question of why the club convergence speed in Europe has been declining. Two possibilities seem likely: first, the strength of club convergence is declining in general; and second, the strength of club convergence is declining for the clubs detected, but club convergence still holds.

To answer this question, we created a new panel containing only the club core regions of the EU-15 panel as identified in Section 5.4.2. Transition and diverging regions and the regions of club core 6 are not considered to increase the statistical reliability of the results. This new panel consists of 45 regions. Step 1 of the CCI procedure is performed for rolling windows of 20 years. This procedure is similar to the one in Section 5.4.4, but this time clubs are not predetermined; instead, the number of clubs and the individual club membership of each region are recorded for each rolling window.

Figure 5.2 illustrates the results of this procedure. The club naming scheme refers to the five club cores identified in the EU-15 panel over the whole period (once again, the two regions of core 6 were not included in the new panel). Four convergence clubs are detected in the first 20-year rolling window (1980–1999). Until 2006, the overall number of clubs remains stable; however, club core 3 increased in size at the expense of club core 4. The latter split into two clubs in 2007. In 2008, some regions separated from club core 3 to constitute club core 2. In 2009 and 2010, further splits occurred, to yield a total of eight clubs in 2011.

These results indicate that heterogeneity across NUTS-1 regions of the EU-15 has increased over the time span considered. In particular, the former two medium-income club cores split up into a range of new clubs, thereby doubling the total number of convergence paths from four to eight. The strength of club convergence has apparently declined within

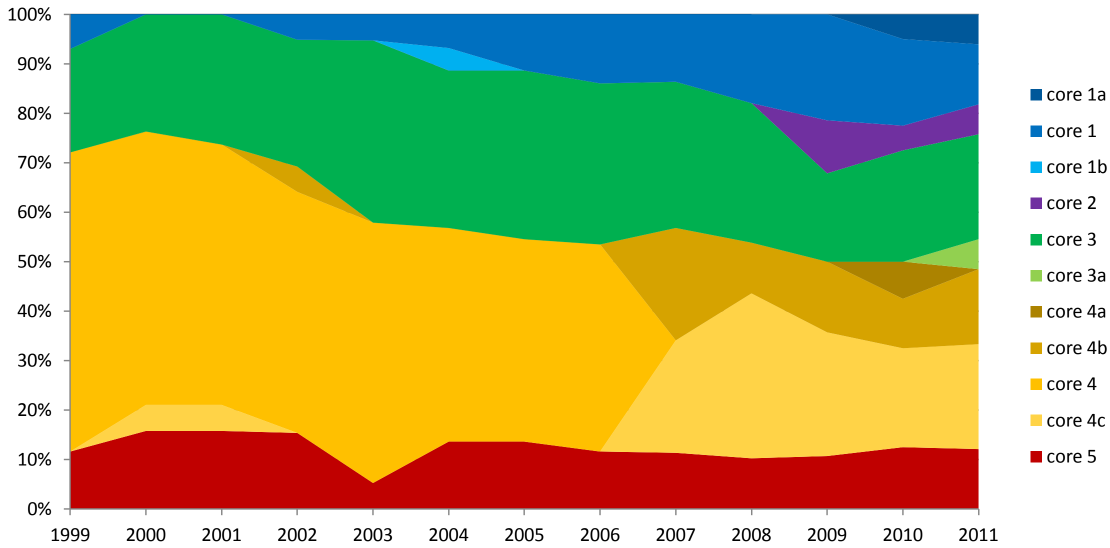

Fig. 5.2: EU-15 panel: development of the size and composition of club cores. Core 6 is not considered.

current clubs; but the relevance of club convergence for overall growth patterns in Europe has strongly increased.

5.5 Concluding Remarks

The starting point for this study was the PS log t test, which checks for club convergence in the presence of transitional and individual heterogeneity. Phillips and Sul (2007) proposed a clustering algorithm and a club merging rule (Phillips and Sul, 2009), and the latter was formalized by Lyncker and Thoennessen (2017). One weakness of the PS procedure lies in the clustering of weak convergence clubs with non-significant parameter estimates, which are not appropriate for any further inference. In Section 5.3.5, it is argued that this feature is caused by a clustering that might be statistically justified (via the log t test) but that potentially changes the club parameter estimates in terms of height, significance, and stability. Therefore, we proposed a four-step procedure to identify the maximum number of clubs for a panel, the club core regions, and representative and stable convergence speeds for the clubs. The CCI procedure is based on the HC algorithm proposed by Lyncker (2016).

In Section 5.4.1, the original PS clustering procedure (Phillips and Sul, 2007, extended by the club merging algorithm as proposed by Lyncker, 2016) and the HC algorithm (Lyncker, 2016) are applied to a panel and two subpanels of data for income per capita in 68 NUTS-1 regions over the period 1980–2011. Subsequently, the CCI procedure proposed in Section 5.3.5 is performed. Finally, Sections 5.4.4, 5.4.5, and 5.4.6 describe the development of the club core convergence speed and the stability of club core compositions.

Results for the initial PS and HC clustering point to the presence of three to four convergence clubs in the EU-15 and in the eurozone panel, and two convergence clubs in the non-eurozone panel. The CCI procedure reveals that six convergence clubs actually exist in the EU-15, which subsequently amalgamate to three clubs for lower critical t-values, as found by the initial HC clustering. A maximum of five clubs are found in the eurozone panel, whereas the non-eurozone panel is indeed characterized by two convergence clubs. Figure 5.3 shows that most NUTS-1 regions in Western and Northern Europe are core regions of the medium-income clubs (clubs 2–4), whereas southern peripheral regions either diverge or follow the growth path of the two low-income clubs (clubs 5 and 6). A substantial number of regions in Spain, Italy, and the UK are in transition towards one of the clubs. The speed of club convergence in the extended club cores of the EU-15 panel ranges from 17% to 61%. When the panel length is shortened to a rolling window of 20 years, the convergence speed within clubs substantially decreases over the last 13 years of observations. When the rolling window is decreased to 4 years, endogenous break tests and regression analysis indicate that the downward trend in convergence speed started in 1997 or 2003. Finally, when the CCI procedure is conducted on the panel of core regions with a rolling window of 20 years, the number of clubs doubles over the last 13 years.

The presence of six regional club convergence clusters (i.e., club cores) in the EU-15 and five in the eurozone illustrates the heterogeneity in growth structure across Europe. Within clubs, convergence has occurred at a fast rate. Owing to the conceptual difference between conditional and club convergence, this speed of club convergence should not be compared to the often-reported growth convergence rate of 2% (Abreu et al., 2005); it should rather be interpreted as evidence of the homogeneity within clubs. However, the decrease in the speed of club convergence over the last years indicates that the strength of existing growth clusters is dwindling. Unfortunately, this development is not caused by a general decrease in the relevance of club convergence, but by fragmentation of existing clubs, which also explains the increase in diverging forces in the whole EU-15 panel. Hence, heterogeneity is increasing not only within the six clubs detected but also within the whole EU-15.

From a policy perspective, the evidence presented here is alarming. Despite enormous efforts to foster convergence in Europe, NUTS-1 regions are becoming more heterogeneous than ever before. The importance of club convergence, which stands at odds to achievement of absolute convergence, is actually increasing rather than decreasing. Since structural breaks in convergence speed and the start of the club core fragmentation occurred before 2008, the financial crisis and the euro crisis cannot explain these developments, although they most likely have spurred them. There is at least some evidence that eurozone membership is not directly responsible for the increase in heterogeneity, since an increase in diverging forces from 2003 onwards can also be observed in the non-eurozone panel.

In further research the methodology proposed here could be applied to different regional panels, for example to NUTS-2 regions. The results of the CCI procedure might be a starting point for an investigation of underlying convergence factors. Given the structural breaks identified in Section 5.4.5, questions such as whether political shocks and shifts (e.g. introduction of the euro and redirection of cohesion funds to the new eastern European regions after 2004) have accelerated diverging forces in the EU-15 might warrant more detailed analysis.

5.6 Appendix

Table 5.8: Eurozone panel: results of different clustering procedures.

method	crit. t-value	club	club size	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg. inc. 1980	avg. inc. 2011	no. div. reg.
log t	-1.65	1	52	-0.587 (0.072)	-8.208	-0.294	17.199	24.703	-
PS	-1.65	1	21	-0.120 (0.149)	-0.807	-0.060	19.776	31.607	1
(c=0)		2	24	0.042 (0.065)	0.645	0.021	15.715	21.115	
		3	6	0.131 (0.291)	0.452	0.066	11.907	12.896	
PS	-1.65	1	2	-1.163 (1.077)	-1.080	-0.581	32.316	53.918	0
(c=100)		2	10	0.425 (0.058)	7.368	0.212	22.793	34.427	
		3	34	-0.168 (0.119)	-1.421	-0.084	15.806	22.300	
		4	6	0.013 (0.266)	0.048	0.006	10.737	12.376	
HC	-1.65	1	10	0.367 (0.092)	3.989	0.184	25.211	36.804	1
		2	30	0.039 (0.075)	0.523	0.020	16.519	23.605	
		3	11	-0.111 (0.203)	-0.550	-0.056	10.977	13.733	
HC	6.5	1	5	1.009 (0.139)	7.234	0.504	31.263	40.345	15
	(=t^{min})	2	4	1.215 (0.101)	12.036	0.607	20.137	31.567	
		3	16	0.295 (0.042)	7.010	0.148	18.019	26.108	
		4	6	0.483 (0.066)	7.307	0.242	13.414	19.482	
		5	6	1.196 (0.127)	9.417	0.598	10.441	14.140	

Notes: *PS*: PS (2007) clustering algorithm with club merging algorithm as proposed in Lyncker and Thoennessen (2015). c: critical value to be set in the PS procedure. *HC*: hierarchical clustering as proposed in Lyncker (2016).

Table 5.9: Non-eurozone panel: results of different clustering procedures.

method	crit. t-value	club	club size	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg. inc. 1980	avg. inc. 2011	no. div. reg.
log t	-1.65	1	16	-0.528 (0.093)	-5.665	-0.264	14.901	27.039	
PS	-1.65	1	13	-0.119 (0.166)	-0.718	-0.060	14.678	26.401	1
(c=0)		2	2	-0.679 (2.115)	-0.321	-0.340	12.055	20.742	
PS	-1.65	1	3	1.138 (0.284)	4.003	0.569	17.875	32.676	1
(c=100)		2	12	-0.358 (0.224)	-1.596	-0.179	13.441	23.889	
HC	-1.65	1	8	0.144 (0.134)	1.069	0.072	15.884	28.734	1
		2	7	-0.111 (0.092)	-1.212	-0.056	12.550	22.118	
HC	8.5	1	3	1.428 (0.166)	8.579	0.714	16.149	29.582	7
	(=t^{min})	2	4	0.753 (0.076)	9.947	0.377	12.744	22.445	

Notes: *PS*: PS (2007) clustering algorithm with club merging algorithm as proposed in Lyncker and Thoennessen (2015). c: critical value to be set in the PS procedure. *HC*: hierarchical clustering as proposed in Lyncker (2016).

Table 5.10: EU-15 panel: regions and club classification.

code	country	regions name	Eurozone	club EU-15	core EU-15	club EZ	core EZ	club non-EZ	core non-EZ
BE1	BE	BRUXELLES-CAPITALE	YES	1	YES	1	YES	-	-
DE5	DE	BREMEN	YES	1	YES	1	YES	-	-
DE6	DE	HAMBURG	YES	1	YES	1	YES	-	-
FR1	FR	ÎLE DE FRANCE	YES	1	YES	1	YES	-	-
IE0	IE	IRELAND	YES	1	YES	1	YES	-	-
SE1	SE	ÖSTRA SVERIGE	NO	1	YES	-	-	div.	
UKI	UK	LONDON	NO	1	YES	-	-	div.	
FI2	FI	ÅLAND	YES	1	NO	div.		-	-
AT3	AT	WESTÖSTERREICH	YES	2	YES	2	YES	-	-
DE2	DE	BAYERN	YES	2	YES	2	YES	-	-
DE7	DE	HESSEN	YES	2	YES	2	YES	-	-
NL3	NL	WEST-NEDERLAND	YES	2	YES	2	YES	-	-
AT1	AT	OSTÖSTERREICH	YES	3	YES	3	YES	-	-
AT2	AT	SÜDÖSTERREICH	YES	3	YES	3	YES	-	-
BE2	BE	VLAAMS GEWEST	YES	3	YES	3	YES	-	-
DE1	DE	BADEN-WÜRTTEMBERG	YES	3	YES	3	YES	-	-
DEA	DE	NORDRHEIN-WESTFALEN	YES	3	YES	3	YES	-	-
DEC	DE	SAARLAND	YES	3	YES	3	YES	-	-
ES3	ES	COMUNIDAD DE MADRID	YES	3	YES	3	NO	-	-
FI1	FI	MANNER-SUOMI	YES	3	YES	3	YES	-	-
NL2	NL	OOST-NEDERLAND	YES	3	YES	3	YES	-	-
NL4	NL	ZUID-NEDERLAND	YES	3	YES	3	YES	-	-
SE2	SE	SÖDRA SVERIGE	NO	3	YES	-	-	div.	
SE3	SE	NORRA SVERIGE	NO	3	YES	-	-	div.	
UKM	UK	SCOTLAND	NO	3	YES	-	-	1	YES
DE9	DE	NIEDERSACHSEN	YES	3	NO	3	NO	-	-
DEB	DE	RHEINLAND-PFALZ	YES	3	NO	4	YES	-	-
DK0	DK	DANMARK	NO	3	NO	-	-	1	YES
ES2	ES	NORESTE	YES	3	NO	4	YES	-	-
FR7	FR	CENTRE-EST	YES	3	NO	3	NO	-	-
ITC	IT	NORD-OVEST	YES	3	NO	3	NO	-	-
ITH	IT	NORD-EST	YES	3	NO	3	NO	-	-
NL1	NL	NOORD-NEDERLAND	YES	3	NO	3	NO	-	-
UKF	UK	EAST MIDLANDS (ENGLAND)	NO	3	NO	-	-	div.	
UKH	UK	EAST OF ENGLAND	NO	3	NO	-	-	div.	
UKJ	UK	SOUTH EAST (ENGLAND)	NO	3	NO	-	-	1	YES
UKK	UK	SOUTH WEST (ENGLAND)	NO	3	NO	-	-	div.	
DEF	DE	SCHLESWIG-HOLSTEIN	YES	4	YES	div.		-	-
ES5	ES	ESTE	YES	4	YES	div.		-	-
FR2	FR	BASSIN PARISIEN	YES	4	YES	div.		-	-
FR3	FR	NORD - PAS-DE-CALAIS	YES	4	YES	div.		-	-
FR4	FR	EST	YES	4	YES	div.		-	-
FR5	FR	OUEST	YES	4	YES	3	NO	-	-
FR6	FR	SUD-OUEST	YES	4	YES	div.		-	-
FR8	FR	MÉDITERRANÉE	YES	4	YES	div.		-	-
ITI	IT	CENTRO (IT)	YES	4	YES	div.		-	-
UKC	UK	NORTH EAST (ENGLAND)	NO	4	YES	-	-	div.	
UKD	UK	NORTH WEST (ENGLAND)	NO	4	YES	-	-	2	YES
UKE	UK	YORKSHIRE AND THE HUMBER	NO	4	YES	-	-	2	YES
UKG	UK	WEST MIDLANDS (ENGLAND)	NO	4	YES	-	-	2	YES
UKL	UK	WALES	NO	4	YES	-	-	div.	
UKN	UK	NORTHERN IRELAND	NO	4	YES	-	-	2	YES
BE3	BE	RÉGION WALLONNE	YES	4	NO	4	YES	-	-
EL3	EL	ATTIKA	YES	4	NO	4	YES	-	-
ES1	ES	NOROESTE	YES	4	NO	4	YES	-	-
EL4	EL	AEGEAN ISLANDS, CRETE	YES	5	YES	5	YES	-	-
ES6	ES	SUR	YES	5	YES	5	YES	-	-
FR9	FR	DÉPARTEMENTS D'OUTRE-MER	YES	5	YES	5	YES	-	-
ITF	IT	SUD	YES	5	YES	5	YES	-	-
ITG	IT	ISOLE	YES	5	YES	5	YES	-	-
PT1	PT	CONTINENTE	YES	5	YES	5	YES	-	-
ES4	ES	CENTRO (ES)	YES	5	NO	4	YES	-	-
ES7	ES	CANARIAS	YES	5	NO	div.		-	-
PT3	PT	REGIÃO AUTÓN. DA MADEIRA	YES	5	NO	div.		-	-
EL1	EL	NORTHERN GREECE	YES	6	YES	div.		-	-
PT2	PT	REGIÃO AUTÓN. DOS AÇORES	YES	6	YES	div.		-	-
EL2	EL	CENTRAL GREECE	YES	div.		div.		-	-
LU0	LU	LUXEMBOURG	YES	div.		div.		-	-

Table 5.11: Eurozone panel: club sizes and convergence speeds ($\hat{\alpha}$) for different t-values.

crit t-value	no. of clubs	no. of div. reg.	Club 1 size ($\hat{\alpha_1}$)	Club 2 size ($\hat{\alpha_2}$)	Club 3 size ($\hat{\alpha_3}$)	Club 4 size ($\hat{\alpha_4}$)	Club 5 size ($\hat{\alpha_5}$)	Club 6 size ($\hat{\alpha_6}$)
-2	3	0	11 (-0.073)		30 (0.020)		11 (-0.056)	
-1	3	1	10 (0.184)		30 (0.020)		11 (-0.056)	
0	4	1	10 (0.184)		30 (0.020)		8 (0.357)	3 (0.761)
1	5	1	10 (0.184)		17 (0.101)	13 (0.346)	8 (0.357)	3 (0.761)
2	5	2	10 (0.184)		17 (0.101)	13 (0.346)	8 (0.357)	2 (1.166)
3	4	4	10 (0.184)		17 (0.101)	13 (0.346)	8 (0.357)	
4	5	5	6 (0.533)	4 (0.607)	17 (0.101)	13 (0.346)	7 (0.380)	
5	5	10	6 (0.533)	4 (0.607)	16 (0.148)	9 (0.324)	7 (0.380)	
6	5	13	6 (0.533)	4 (0.607)	16 (0.148)	7 (0.254)	6 (0.598)	
7	3	26		4 (0.607)	16 (0.148)		6 (0.598)	
8	2	32			14 (0.171)		6 (0.598)	
9	2	33			13 (0.205)		6 (0.598)	
10	1	39			13 (0.205)			
11	1	39			13 (0.205)			
12	1	42			10 (0.338)			
13	1	43			9 (0.371)			
14	1	43			9 (0.371)			
15	1	43			9 (0.371)			
16	1	52						

Notes: Results based on a hierarchical clustering (cp. Section 5.3.4) of the EURO-12 panel. Critical t-value increased in steps of 0.5 (Table depicts integer t-values only). t^{min} identified at 6.5.

Table 5.12: Non-eurozone panel: club sizes and convergence speeds ($\hat{\alpha}$) for different t-values.

crit t-value	no. of clubs	no. of div. reg.	Club 1 size ($\hat{\alpha_1}$)	Club 2 size ($\hat{\alpha_2}$)
-2	1	1	15 (-0.124)	
-1	2	2	8 (0.072)	6 (0.085)
0	2	2	8 (0.072)	6 (0.085)
1	2	2	8 (0.072)	6 (0.085)
2	2	4	7 (0.311)	5 (0.368)
3	2	4	7 (0.311)	5 (0.368)
4	2	4	7 (0.311)	5 (0.368)
5	2	6	5 (0.338)	5 (0.368)
6	2	7	4 (0.385)	5 (0.368)
7	2	8	3 (0.714)	5 (0.368)
8	2	9	3 (0.714)	4 (0.377)
9	1	12		4 (0.377)
10	1	16		

Notes: Results based on a hierarchical clustering (cp. Section 5.3.4) of the non-Euro panel.Critical t-value increased in steps of 0.5 (Table depicts integer t-values only). t^{min} identified at 8.5.

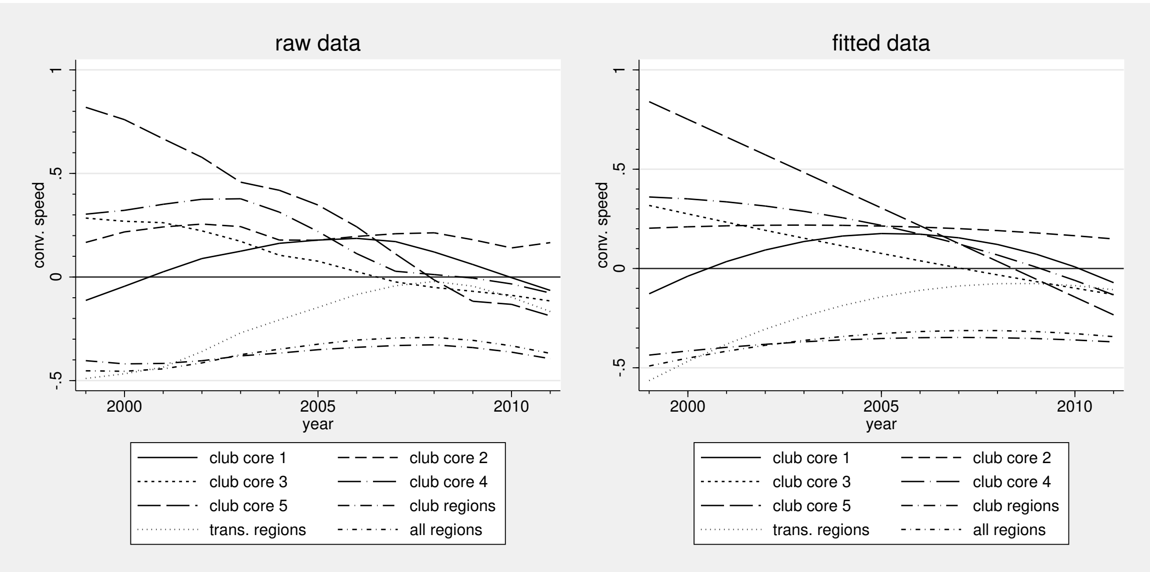

Fig. 5.3: EU-15 panel: development of the convergence speed (moving log t test over 20 years, with the first observation in 1999 for the period 1980–1999). Club 6 is not depicted.

Table 5.13: EU-15 panel: trends and structural breaks in convergence speeds.

group	core 1	core 2	core 3	core 4	core 5	cores	trans.	all
# reg.	7	4	13	15	6	47	19	68
M0								
const.	-1.010***	-0.908***	-0.829***	-0.859***	-0.834***	-0.963***	-0.991***	-0.976***
t	0.004	0.001	-0.005***	-0.003	-0.001	-0.002***	0.000	-0.002
R squ.	0.158	0.003	0.285	0.034	0.002	0.309	0.002	0.134
Q.A.								
F-stat.	19.9***	3.1	5.9***	10.0***	13.9***	11.5***	18.1***	16.2***
break	1997	1991	1991	1993	1992	1997	1997	1997
M1								
const.	-1.084***	-0.801***	-0.807***	-0.832***	-1.289***	-0.933***	-0.935***	-0.941***
D	0.469***	0.031	0.077	0.277**	0.496***	0.057	0.237**	0.090*
t	0.012***	-0.035***	-0.017**	-0.019**	0.096***	-0.008***	-0.011***	-0.008***
Dt	-0.025***	0.030**	0.008	0.003	-0.100***	0.002	-0.001	0.001
R squ.	0.676	0.200	0.514	0.463	0.528	0.640	0.593	0.623
M1 v M0								
F-stat.	50.5***	17.8***	10.3***	16.9***	70.8***	20.4***	27.0***	13.8***
B.P.								
Scaled F.	56.2***	14.1***	26.6***	96.4***	79.0***	68.5***	60.4***	77.9***
break 1	1989	1991	1991	1990	1992	1997	1990	1990
break 2	1997	2008	2004	1995	2001	2005	1998	2003
M2								
const.	-1.127***	-0.801***	-0.807***	-0.831***	-1.289***	-0.933***	-0.985***	-0.952***
D1	-0.058	-0.088	0.177**	-1.529***	0.114	-0.097***	-0.202***	-0.169***
D2	0.571***	-2.356	0.281***	1.693***	-0.486	0.311***	0.565***	0.478***
t	0.029**	-0.035***	-0.017**	-0.017	0.096***	-0.008***	0.006	-0.003
D1t	-0.008	0.038***	0.000	0.166***	-0.068***	0.010***	0.005	0.011***
D2t	-0.034***	0.078	-0.006	-0.161***	0.002	-0.015***	-0.026***	-0.023***
R squ.	0.728	0.383	0.683	0.668	0.757	0.746	0.745	0.809
M2 v M0								
F-stat.	32.0***	8.6***	15.0***	43.3***	42.2***	45.0***	38.2***	46.1***
best fit	**M1**	**M1**	**M2**	**M2**	**M1**	**M2**	**M2**	**M2**

Notes: M0: $speed_t = const. + \gamma \cdot trend + \epsilon_t$. Regressions based on OLS with HAC-standard errors (Bartlett-Kernel with Newey-West fixed bandwidth). Q.A.: Quandt-Andrews endogenous break test (using max. LR F-stat.). B.P.: Bai-Perron multiple break test (significance based on scaled F-stat.). 'best fit' based on p-values of Wald F-stat. (M1 v M0 & M2 v M0). 'core 6' (2 reg.) not reported. ***p<0.01, **p<0.05, *p<0.1. Tests performed with Stata12 & Eviews9.

Table 5.14: Eurozone panel: trends and structural breaks in convergence speeds.

group	core 1	core 2	core 3	core 4	core 5	cores	trans.	all
# reg.	6	4	9	7	6	32	7	52
M0								
const.	-0.926***	-0.908***	-0.863***	-0.926***	-0.834***	-0.959***	-0.912***	-0.983***
t	0.001	0.001	-0.003	-0.001	-0.001	-0.002*	-0.001	-0.001
R squ.	0.003	0.003	0.068	0.009	0.002	0.249	0.002	0.068
Q.A.								
F-stat.	11.6***	3.1	5.1*	15.8***	13.9***	11.1***	2.3	18.3***
breaks	1996	1991	1988	2002	1992	2003	2007	1997
M1								
const.	-0.890***	-0.801***	-0.696***	-0.961***	-1.289***	-0.965***	-0.904***	-0.946***
D	0.360***	0.031***	-0.130***	0.760***	0.496***	0.365***	-2.110***	0.114**
t	-0.010	-0.035***	-0.070***	0.003	0.096***	-0.002*	-0.001	-0.009***
Dt	-0.006	0.030**	0.066***	-0.033***	-0.100***	-0.015***	0.078***	0.001
R squ.	0.484	0.200	0.339	0.563	0.528	0.602	0.156	0.622
M1 v M0								
F-stat.	15.7***	17.8***	32.9***	118.4***	70.8***	20.5***	6.9***	12.5***
B.P.								
Scaled F.	43.7***	14.1***	38.1***	106.9***	79.0***	144.4***	11.9**	59.7***
break 1	1987	1991	1988	1987	1992	1993	1998	1990
break 2	1997	2008	2004	2002	2001	2007	2008	2004
M2								
const.	-0.651***	-0.801***	-0.696***	-0.902***	-1.289***	-0.964***	-0.836***	-0.967***
D1	-0.383***	-0.088	-0.082	-0.013	0.114	-0.091***	0.215	-0.178***
D2	0.573***	-2.356	0.695***	0.715***	-0.486	0.741***	-3.972***	0.568***
t	-0.104***	-0.035***	-0.070***	-0.032***	0.096***	-0.001	-0.012**	-0.001
D1t	0.111***	0.038***	0.061***	0.032***	-0.068***	0.005*	-0.001	0.010***
D2t	-0.026***	0.078	-0.023**	-0.030***	0.002	-0.031***	0.147***	-0.027***
R squ.	0.634	0.383	0.577	0.655	0.757	0.739	0.392	0.817
M2 v M0								
F-stat.	23.2***	8.6***	21.6***	69.6***	42.2***	105.7***	9.3***	34.3***
best fit	**M2**	**M1**	**M1**	**M1**	**M1**	**M2**	**M2**	**M2**

Notes: cp. Table 5.13.

Table 5.15: Non-eurozone panel: trends and structural breaks in convergence speeds.

group	core 1	core 2	cores	all
# reg.	3	4	7	16
M0				
const.	-0.893***	-0.984***	-0.931***	-0.937***
t	0.001	0.003	-0.002	-0.004**
R squ.	0.007	0.012	0.069	0.231
Q.A.				
F-stat.	7.7***	13.8***	16.0***	6.5**
breaks	2003	1990	1993	1988
M1				
const.	-0.907***	-0.462***	-0.949***	-0.855***
D	1.307***	-0.369***	0.244***	-0.036
t	0.002	-0.152***	-0.007***	-0.045***
Dt	-0.051***	0.149***	-0.006	0.039***
R squ.	0.386	0.531	0.592	0.495
M1 v M0				
F-stat.	21.7***	43.3***	24.7***	21.4***
B.P.				
Scaled F.	19.4***	1970.8***	58.6***	316.5***
break 1	1993	1988	1993	1987
break 2	2003	1992	2003	1996
M2				
const.	-0.891***	-0.587***	-0.949***	-0.823***
D1	0.331**	-3.069***	0.398***	-0.276***
D2	0.961***	2.867***	0.156	0.160**
t	-0.006	-0.096***	-0.007**	-0.061***
D1t	-0.014	0.418***	-0.017***	0.078***
D2t	-0.030**	-0.328***	-0.001	-0.021***
R squ.	0.506	0.675	0.734	0.663
M2 v M0				
F-stat.	16.1***	1247.6***	53.6***	399.3***
best fit	**M2**	**M2**	**M2**	**M2**

Notes: cp. Table 5.13.

Chapter 6

Regional Club Convergence in the EU: Evidence from a Panel Data Analysis

We investigate club convergence in income per capita in 194 European NUTS-2 regions using a nonlinear, time-varying factor model that allows for individual and transitional heterogeneity. Moreover, we extend an existing club clustering algorithm with two post-clustering merging algorithms that finalize club formation. We also apply an ordered response model to assess the role of initial and structural conditions, as well as geographic factors. Our results indicate the presence of four convergence clubs in the EU-15 countries. In support of the club convergence hypothesis, we find that initial conditions matter for the resulting income distribution. Geographic clustering is quite pronounced; besides a north-to-south division we detect high-income clusters for capital cities. We conclude that the main supranational policy challenge is the politically-sensitive handling of a multi-speed Europe.

JEL classification: C23, C50, R11, O47

Keywords: club convergence, regional development, log t test

[0] Co-authored with Rasmus Thönnessen. The final publication is available at Springer via http://dx.doi.org/10.1007/s00181-016-1096-2. We gratefully acknowledge three anonymous referees for valuable comments on two earlier drafts. We also thank the participants of the 8th RGS Doctoral Conference on Economics in February 2015 for helpful comments.

6.1 Introduction

Regional convergence is an important topic in the political agenda of the European Union (EU). In the financial framework for 2007–2013, cohesion expenditure amounted to 350 billion euro, representing 36% of the EU budget (European Commission, 2016). A central argument in favor of European cohesion and integration is that all regions should be enabled to enter a common growth path, thereby generating economic gains for every EU citizen. Thus, a pivotal question is whether European integration has led to per capita income convergence. However, absolute income convergence might be virtually beyond reach in the presence of club convergence. This concept was put forward by Azariadis and Drazen (1990), Azariadis (1996), and Galor (1996) and essentially states that a region's long run growth path is also determined by initial conditions. Hence, questions on whether regions in the EU converge to the same income level or constitute convergence clubs are highly relevant for policy-makers and academics.

Income convergence as a theoretical concept is related to neoclassical growth theory, according to which income between units converges as long as structural characteristics are the same, regardless of the initial level of income and capital stock. Besides Baumol (1986), who were the first to test for income catch-up processes, methodological landmarks have been achieved by Barro and Sala-i Martin (1992) and Mankiw et al. (1992), who translated the Solow model into an empirical test for convergence. Islam (1995) eventually proposed a panel specification of the Solow model. These regression approaches allow the detection of converging behavior in a group of units whose technological progress evolves homogeneously across time and units.

If technological progress is actually heterogeneous across units, the assumption of a homogeneous slope coefficient will lead to inconsistent parameter estimates (Robertson and Symons, 1992; Pesaran and Smith, 1995). Proposals to overcome this inconsistency problem include nonparametric and semiparametric approaches (Li and Stengos, 1996; Baltagi and Li, 2002; Cai and Li, 2008), and incorporation of a country-specific production function into the augmented Solow model (Durlauf et al., 2001). Phillips and Sul (2003) widened the discussion and pointed to the important role of heterogeneity over time. They later proposed a nonlinear time-varying factor model that accommodates individual and transitional heterogeneity (hereafter called the PS model; Phillips and Sul, 2007). In this context, factor representation circumvents potential endogeneity and omitted variable bias, which might arise in the use of a steady-state proxy vector (Phillips and Sul, 2009).

The aim of the present study is to find convergence patterns in per capita GDP for 194 NUTS-2 regions in the EU-15. To take heterogeneous technological progress into account, we use the PS factor model and the PS convergence and cluster methodology. Factorization allows separation of unit-specific transitional factors from common factors to reveal the long-run growth trend for the underlying time series. We augment the existing club clustering algorithm of Phillips and Sul (2007, 2009) with two post-clustering merging algorithms to improve and complete the decision rules for club formation. This novel extension avoids ambiguity in the club merging process proposed by Phillips and Sul (2009). We then analyze the factors influencing membership of a certain club using an ordered response model as proposed by Bartkowska and Riedl (2012). We test the club convergence hypothesis stating that units with similar structural characteristics converge in the long-run if initial conditions are in the same basin of attraction (Galor, 1996). Unlike previous work, the ordered response model is augmented with further geographic explanatory variables.

Our results indicate strong and robust evidence in favor of four convergence clubs in the EU-15 countries. The ordered response model confirms the pivotal role of initial factors and hence corroborates the club convergence hypothesis. We also find a clear regional north-to-south decline in income, as well as a strong effect of capital cities. Overall, our results contribute to existing research on European income convergence that also uses the PS procedure but mainly draws on national data (Apergis et al., 2010; Fritsche and Kuzin, 2011; Monfort et al., 2013; Borsi and Metiu, 2015).

The remainder of the paper is organized as follows. Section 6.2 gives an overview of empirical studies on national and regional convergence in Europe. Our estimation strategy, which follows and extends the PS methodology, is outlined in Section 6.3. Results for the log t tests and the ordered logit model are provided in Section 6.4, followed by robustness tests in Section 6.5. Section 6.6 contains a summary of our findings and some concluding remarks.

6.2 Literature on European Regional Convergence

A number of empirical studies on economic growth adopt the nonlinear time-varying PS factor model to determine convergence clubs. Out of these studies, several authors have investigated income convergence within Europe (see Table 6.1 for an overview). Borsi and Metiu (2015) use national income per capita data for the EU-27 and find no absolute convergence, but club convergence, with the formation of four convergence clubs. Their sample also includes the newly joined countries from Eastern and Central Europe. Clubs are formed along geographic regions (in particular, southeast vs. northwest), but are not linked to eurozone membership.

Monfort et al. (2013) investigate national income per worker in the EU-27 (except for Luxembourg, Malta, and Cyprus). They find four convergence clubs, of which two belong to the EU-15 and two to the new Eastern European members. For the two EU-15 clubs, they do not find any clustering along geographic lines or with respect to eurozone membership. However, the latter factor seems to play a role in the clustering of the two Eastern European clubs.[1] Two convergence clubs within the EU-15 are also detected by Apergis et al. (2010), who use national income per capita data. One of these clubs consists of the so called GIPS countries[2] plus Germany, which is clearly a remarkable if not questionable result in light of recent developments in the eurozone. Overall, heterogeneity with respect to technological conditions in general and labor productivity in particular are identified as the most decisive factors for the absence of absolute convergence. Fritsche and Kuzin (2011) investigate convergence in prices, labor costs, productivity, and income per capita among EU-15 countries. With respect to income, they find three convergence clubs, with Italy and Germany not belonging to any of these clusters.

Despite these studies at the national level, application of the PS procedure at the regional level is rare, which surprises in light of the importance of European regional development for policy makers. An exception is the study by Bartkowska and Riedl (2012), who apply the PS log t test and clustering method for 206 NUTS-2 regions over the period 1990–2002. They identify six convergence clubs, but cannot reject convergence across subsequent ordered fractions of neighboring clubs. Moreover, using an ordered logit model, they reveal that initial conditions do play a role, indicating the applicability of the club convergence hypothesis.

The PS factor model is usually applied to aggregate income data. Hence, the role of sectoral dynamics (Fiaschi and Lavezzi, 2007) is neglected. Furthermore, the methodology does not explicitly model spatial interaction, which is in particular relevant with respect to spatial dynamics in the accumulation of knowledge. However, the appealing feature of the PS method is that growth determinants and spatial influences are captured in a more flexible way, with both common and idiosyncratic factor loadings.

In light of the importance of spatial factors, we provide a brief summary of regional convergence research adopting methodologies *other* than the PS factor model. One strand of the literature examines regional convergence using variations of the regression approach of Barro and Sala-i Martin (1992). For example, Fischer and Stirböck (2006) determine club convergence within a spatial econometric framework for 256 NUTS-2 regions over the period 1995–2000. Their three-step procedure includes local clustering as proposed by

[1] Nevertheless, Monfort et al. (2013) do not establish any causality running from eurozone membership to a higher growth path. It seems more reasonable to assume that certain economic characteristics of these countries qualified them to join the eurozone.

[2] GIPS refers to Greece, Italy, Portugal, and Spain.

Table 6.1: Convergence literature using the log t test for European data.

Author(s)	**Level (per)**	**Units (Time span)**	**EU-15/ CEEC**	**Number of Clubs (geographic pattern)**
Apergis et al. (2010)	national (capita)	14 (1980-2004) 14 (1990-2004)	yes / no yes / no	1 (only Greece diverging) 2 (GIPS+Germany vs. rest)
Fritsche & Kuzin (2011)	national (capita)	15 (1960-2006)	yes / no	3 (no clear pattern)
Montfort et al. (2013)	national (worker)	14 (1980-2009) 24 (1990-2009) 10 (1990-2009)	yes / no yes / yes no / yes	2 (core vs. periphery) 2 (W vs. E) 2 (Euro zone vs. rest)
Borsi & Metiu (2014)	national (capita) national (capita) national (capita)	21 (1970-2010) 21 (1995-2010) 27 (1995-2010)	yes / yes yes / yes yes / yes	4 (W vs. E) 4 (NW vs. SE) 4 (NW vs. SE)
Bartkowska & Riedl (2012)	NUTS-2 (worker)	206 (1990-2002)	yes / no	6 (core vs. periphery; N vs. S)

Getis and Ord (1992), standard Barro-style convergence testing within the clusters, and a test of a spatial error specification. They find evidence of the presence of two spatial regimes. Procedures comprising spatial filtering techniques before the actual regression analysis are also proposed by Badinger et al. (2004) and Battisti and Vaio (2008) with, however, differing results: across European NUTS-2 regions, Badinger et al. (2004) find evidence for conditional convergence, whereas Battisti and Vaio's (2008) mixture regression approach suggests that the majority of European regions shows no tendency to converge.

Ramajo et al. (2008) explicitly consider spatial heterogeneity and spatial autocorrelation in their regression framework. They find that regions in Ireland, Greece, Portugal, and Spain (so-called cohesion-fund countries) converged separately compared to the rest of the EU in the period 1981–1996. Postiglione et al. (2010) use a modified regression tree approach (Durlauf and Johnson, 1995), which takes spatial autocorrelation into account. They identify five convergence clubs across 191 NUTS-2 data over the period 1980–2002. More recently, Postiglione et al. (2013) have employed a spatial Durbin model as an objective function of two clustering algorithms. In a panel of 187 NUTS-2 regions from 1981 to 2004, they find four convergence clubs.

Other researchers do not explicitly consider spatial factors. For example, Lopez-Rodriguez (2008) adopts a fixed-effects panel data regression model to assess convergence in Europe at different regional levels (NUTS-1, -2, -3) over the period 1982–1999. He shows that regional steady-state incomes changed over time and drifted apart, leading to overall divergence in Europe, although the conditional convergence relationship might hold. Different cross-section and panel specifications used by Arbia et al. (2008) show that the inclusion of spatial factors does not necessarily lead to different results. Moreover, all of their approaches indicate that convergence across 183 European NUTS-2 regions cannot be rejected.

Besides the regression approach, regional convergence tests have also been based on distributional dynamics and on unit root and cointegration methods. Fiaschi and Lavezzi (2007) show that the distribution of labor productivity has two peaks, which implies two income clubs across NUTS-2 regions during 1980–2002. Furthermore, they investigate the determinants of club membership via descriptive statistics and nonlinear regression. Fischer and Stumpner (2008) apply a model of distribution dynamics to 257 NUTS-2 regions of the EU-27 over the period 1995–2003. They extend an existing distribution approach framework to spatially filtered kernel estimation and thereby identify two groups, with the high-income metropolitan group growing faster than the group comprising the other regions. Canova (2004) proposes a clustering methodology based on predictive densities. His methodology is a unified approach that is rooted in the tradition of Bayesian inference. However, it does not allow for spatial dependencies. Similarly, Crespo Cuaresma and Feldkircher (2013) use a Bayesian model averaging method to detect convergence clubs.

Another important contribution is made by Corrado et al. (2005), who use a multivariate stationarity test to endogenously identify regional club clustering. The method explicitly detects the impact of spatial factors, including knowledge spillovers from neighboring regions. In the context of knowledge accumulation, Olejnik (2008) uses a spatial autoregressively distributed lag model for 228 NUTS-2 regions and illustrates the importance of considering spatial interaction in regional growth analyses and the pivotal role of human capital as a factor for growth.

In comparison to the PS methodology, most of the (spatial) studies mentioned above do not consider technological heterogeneity across both, regions and time. Given this fact and our potentially heterogeneous panel, we believe that the PS method is most appropriate for detecting convergence clusters.

6.3 Estimation Strategy

6.3.1 log t Convergence Test

Phillips and Sul (2007) explain log income as the product of a time-varying idiosyncratic factor loading δ_{it}, which also absorbs the error terms ϵ_{it}, and a common factor μ_t, which determines the common growth path, according to the relation

$$\log y_{it} = \delta_{it}\mu_t, \tag{6.1}$$

where δ_{it} acts as a unit-specific measure of the share of or distance to the common growth path μ_t. Clearly, it will change size in transition to the common growth path. For subsequent hypothesis testing, the relative transition coefficient h_{it} needs to be constructed, given by log income for a unit in relation to the panel average at time t:

$$h_{it} = \frac{\log y_{it}}{N^{-1}\sum_{i=1}^{N}\log y_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N}\delta_{it}}. \tag{6.2}$$

As Eq. (6.2) shows, the common component μ_t drops out, so h_{it} is defined as the relation of the factor loading δ_{it} for a unit to the average δ_t.

Convergence implies that an individual unit approaches the sample average over time. Therefore, it holds that the transition coefficient δ_{it} converges towards δ as $t \to \infty$. This is equivalent to convergence of the relative transition coefficient h_{it} towards unity as $t \to \infty$. The latter in turn implies that the cross-sectional variance of h_{it}, H_t, converges towards zero as $t \to \infty$. In summary, convergence in a panel is given by the following conditions:

$$\delta_{it} \to \delta \text{ for all } i \text{ as } t \to \infty \tag{6.3}$$

$$h_{it} \to 1 \text{ for all } i \text{ as } t \to \infty \tag{6.4}$$

$$H_t = N^{-1}\sum_{i=1}^{N}(h_{it}-1)^2 \to 0 \text{ for all } i \text{ as } t \to \infty. \tag{6.5}$$

However, these three equations need to be treated with caution. The cross-sectional variance of a sample might decrease even if there is no overall convergence and only local convergence within certain subgroups. To account for such potential nonstationary transitional behavior, Phillips and Sul (2007) propose the following semiparametric specification of δ_{it}:

$$\delta_{it} = \delta_i + \sigma_i \xi_{it} L(t)^{-1} t^{-\alpha}, \tag{6.6}$$

where δ_i is the time-invariant part of the country-specific factor loading δ_{it}, $L(t)$ is a slowly varying increasing function (with $L(t) \to \infty$ as $t \to \infty$), α is the decay rate (i.e., the speed of convergence), and ξ_{it} is a weakly autocorrelated random error variable (ξ_{it} is $iid(0,1)$).

On the basis of these preliminary considerations, the PS log t convergence test examines the following hypotheses:

$$H_0 : \delta_i = \delta \quad \text{and} \quad \alpha \geq 0 \qquad \text{vs.} \qquad H_1 : \delta_i \neq \delta \quad \text{for all}\, i, \text{ or}\, \alpha < 0. \tag{6.7}$$

The testing procedure involves the following three steps.

1. Calculation of the cross-sectional variance ratio H_1/H_t (cp. equation 6.5).

2. Estimation of the following OLS regression:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \hat{a} + \hat{b}\log t + \hat{u}_t \tag{6.8}$$

$$\text{for } t = [rT], [rT]+1, \ldots, T \text{ for some } r > 0.$$

3. One-sided t test for $\alpha \geq 0$ using $\hat{b}$ ($\hat{b} = 2\hat{\alpha}$) and a HAC standard error.

r ($r \in (0,1)$) is a truncation parameter that shortens the regression by a certain fraction of the first observations. Monte Carlo simulations by Phillips and Sul (2007) suggest the use of $r = 0.3$ and $L(t) = \log t$ for samples up to $T = 50$. Given the assumptions outlined by Phillips and Sul (2007), the standard critical values can be applied such that the null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$.

6.3.2 Club Clustering Algorithm

The log t test is rejected for samples that do not converge overall. Phillips and Sul (2007) developed a club clustering algorithm to detect both convergence clubs and diverging regions. The algorithm consists of the following four steps:

1. Last observation ordering: The panel observations are sorted in descending order with respect to the last observations.

2. Core group formation: The log t test is conducted for the first $k = 2$ regions. If $t_{\hat{b}}(k = 2) > -1.65$, both regions establish the core group G_k. Subsequently, the log t test is conducted for G_k plus the next region. If $t_{\hat{b}}(k = 3) > t_{\hat{b}}(k = 2)$, the region is added to G_k. This procedure is performed as long as $t_{\hat{b}}(k) > t_{\hat{b}}(k-1)$ for all $N > k \geq 2$. If $t_{\hat{b}}(N) > t_{\hat{b}}(N-1)$ the whole remaining panel converges. If $t_{\hat{b}} > -1.65$ does not hold for the first two units chosen, the first unit is dropped and the loop is performed for the remaining units. If $t_{\hat{b}} > -1.65$ does not hold for any two units chosen, the whole panel diverges.

3. Sieve individuals for club membership: After the core group G_k is formed, log t tests on G_k with each remaining unit are conducted. All units for which $t_{\hat{b}}$ is greater than a certain critical value c are pooled in a subgroup. If the log t test on G_k combined with the subgroup is greater than -1.65, all units of the subgroup are added to G_k. If not, the critical value has to be increased and the procedure is repeated.

4. Stopping rule: If by now only one unit is left, this unit diverges. Otherwise, a log t test for all remaining units is conducted. If $t_{\hat{b}} > -1.65$, all remaining units constitute

their own convergence club. If $t_{\hat{b}} < -1.65$, steps 1–3 need to be performed for all remaining units to find another convergence club. If no further convergence club is found, the remaining regions diverge.

6.3.3 Club Merging Algorithm

The number of clubs identified in a given sample depends on choice of the critical value c. A high c value corresponds to conservative sieving for further club members. This in turn might lead to identification of more clubs than actually exist. To remedy this, Phillips and Sul (2009) proposed log t tests for adjacent clubs after the club clustering algorithm. If $t_{\hat{b}} > -1.65$, the respective clubs are merged at the 5% significance level.

For a total number of C initially identified clubs, a total series of $C-1$ log t tests between adjacent clubs needs to be calculated. In this context, it is possible that a sequence of log t tests will not be able to reject the convergence hypothesis. One explanation would be that all clubs in this sequence indeed converge to the same steady-state growth path. However, in the presence of transition across clubs (Phillips and Sul, 2009) it could be possible that a certain club contains elements converging towards the next higher club and elements converging towards the next lower club. Therefore, simple amalgamation of all adjacent clubs with significant t values might form clubs in cases in which the log t test for convergence is rejected. The point becomes clear for the extreme case in which all $C-1$ log t tests between adjacent clubs are significant; only in certain cases is this caused by actual convergence of all clubs. Hence, if the club clustering algorithm identifies many similar clubs (owing to a wide sample or a conservative critical value c), manual ex-post merging might become ambiguous. For these reasons, we propose the following algorithm.

1. Merging vector: Starting with P clubs, a log t test for adjacent clubs is performed to obtain an $(M \times 1)$ vector of convergence test statistics $t_{\hat{b}}$ (with $m = 1, 2, \ldots, M$ and $M = P - 1$).

2. Merging rule: The rule starts with the first element of the club merging vector. If $t_{\hat{b}}(m) > -1.65$ and $t_{\hat{b}}(m) > t_{\hat{b}}(m+1)$, then the two clubs determining $t_{\hat{b}}(m)$ are merged and the algorithm starts again at step 1. If $t_{\hat{b}}(m) < -1.65$ and/or $t_{\hat{b}}(m) < t_{\hat{b}}(m+1)$, the merging rule is then performed for all following pairs of $t_{\hat{b}}(m)$.

3. Last element: If $t_{\hat{b}}(m = M) > -1.65$, the last two clubs are merged.

6.3.4 Merging Algorithm for Diverging Regions

Application of the club clustering and club merging algorithm delivers statistically significant clubs and avoids overdetermination of the number of clubs. However, units identified as diverging according to the PS clustering algorithm might not necessarily be still diverging if the club merging algorithm has formed new clubs. For example, for a given panel, a conservative critical value c in the PS clustering algorithm will lead to the formation of comparatively more clubs. Accordingly, the number of club mergers in the club merging algorithm will be comparatively large. It might well be the case that convergence of formerly diverging regions with the consolidated clubs cannot be rejected by the log t test criterion. In this case, we also need to test whether the remaining diverging regions form their own convergence club. For this purpose, we propose the following algorithm.

1. Divergence club: A log t test for all diverging regions (left) is performed. If $t_{\hat{b}} > -1.65$, the diverging regions form their own club and the algorithm stops.

2. Merging table: A log t test is performed for each diverging region and each club at a time. The results are saved in a $(d \times p)$ matrix, where each row d represents a diverging region and each column p a convergence club.

3. Merging rule: If the highest $t_{\hat{b}}$ in the table is greater than a certain critical value e, the respective diverging region is added to the respective club. Subsequently, the algorithm starts again at step 1.

4. Stopping rule: The algorithm stops as soon as the merging table for diverging regions does not contain any $t_{\hat{b}} > e$. All regions left are truly diverging regions.

For consistency, we set the critical value e equal to the t value at the chosen level of significance ($e = -1.645$ at the 5% significance level).

6.3.5 Ordered Logit Model

The approach of Phillips and Sul (2007) clusters regions according to their transition paths, which are revealed through factorizing the *log* of income. However, this does not prove the club convergence hypothesis (Azariadis and Drazen, 1990; Azariadis, 1996; Galor, 1996). For this reason, we follow Bartkowska and Riedl (2012), who propose a two-step procedure: the first step is the PS clustering and the second is application of an ordered logit model to identify variables that drive club formation. The club convergence hypothesis postulates that the starting conditions matter for the income distribution of an economy. By contrast, conditional convergence studies suggest that structural characteristics (such as time preferences or economic policy) determine the long-run growth path, independent of the starting conditions. On the basis of these theoretical considerations, we include both the initial conditions and the structural characteristics as variables in the regression equation to find the determinants of clustering. To strengthen robustness, we also control for geographic factors.

The ordered logit model assigns each region to one convergence club, denoted as $c = 1, \ldots, C$, which is a categorical variable. We model the determinants of region membership to one of these C alternatives. The alternatives can be ranked in a logical way according to the steady-state per capita income of each club. We assume that there is an underlying latent variable that drives the choice between different clubs. This is consistent with a latent variable equation of the form

$$y_i^* = x_i^{'} \beta + \varepsilon_i, \tag{6.9}$$

where y_i^* is the unobserved dependent variable and ε_i has a logistic distribution.[3] The observed variable is the ordinal variable $y_i = 1, \ldots, C$, corresponding to $y_i^* < \gamma_1, \gamma_1 \leq y_i^* < \gamma_2, \ldots$ and $y_i^* \geq \gamma_C$ respectively. The joint estimation of the unknown parameters γ and β is based on maximum likelihood (ML).

The vector x_i includes the potential determinants of club membership by region i and a constant term. In contrast to their sign, the size of the coefficients β has no sensible economic interpretation. Therefore, we compute the implied probability that a given region belongs to a certain convergence club (e.g., to Club $c = 4$), which is called the predicted probability. It follows from the logistic distribution that the probability is given by

$$P\{y_i = 4 \,|\, x_i\} = \frac{1}{1 + exp(-\gamma_3 + x_i^{'} \beta)} - \frac{1}{1 + exp(-\gamma_2 + x_i^{'} \beta)}. \tag{6.10}$$

Predicted probabilities are evaluated for the means of all remaining variables and are hence higher the larger a club is and the closer it is to the sample average. To assess the importance of certain variables in determining club membership, we calculate the marginal effects of the predicted probabilities. The marginal effects estimate how a unit change in the explanatory variable changes the probability that an average region belongs to the respective club, while holding all other variables fixed at their sample averages. Lastly, as a goodness-of-fit measure, we report McFadden's R^2, which is often used as a likelihood ratio index.

[3] Discussions of ordered logit models can be found in Verbeek (2012, chap. 7) and Cameron and Trivedi (2005, chap. 15).

6.3.6 Data

Our main data source is the European Regional Database of Cambridge Econometrics and the variable of interest is gross value added (GVA) per capita at the NUTS-2 level. We use per capita values to focus on cross-unit income convergence. Other studies have used GVA per worker as a measure for productivity. We assess this seemingly small difference as pivotal for estimation results and inference; since a region's GVA and its number of workers are likely to be positively correlated, changes in GVA might simply be caused by changes in the number of workers. Hence, to assess income catch-up and income convergence processes and to infer policy conclusion and welfare considerations, we are advised to use per capita values. Besides Cambridge Econometrics, we use data from the European Transport Policy Information System (ETIS) for average longitude and latitude values for the NUTS-2 regions. Finally, to measure human capital in the ordered logit section, we use a new dataset of Barro and Lee (2013).

Our panel considers 194 regions of 14 EU countries over the period 1980–2011 ($T = 31$). It comprises all member states as of 2003 (the so-called EU-15) except Luxembourg, before Eastern European member states joined the EU. Table 6.2 provides a brief overview of the panel.

Table 6.2: Overview of sample of EU-15 regions, 1980-2011

Country	Eurozone	Obs.	No. of reg.	Mean GVApc	Std.Dev.	CV 1980	CV 2011
Austria	Yes	288	9	21.92	5.66	10.70	19.29
Belgium	Yes	352	11	21.19	8.91	47.90	35.99
Denmark	No	160	5	26.67	5.99	20.40	18.13
Finland	Yes	128	4	22.07	6.35	10.55	27.32
France	Yes	704	22	19.29	4.09	16.42	18.28
Germany	Yes	960	30	23.47	4.88	18.76	18.91
Greece	Yes	416	13	11.96	2.75	30.38	22.65
Ireland	Yes	64	2	23.43	7.79	14.97	34.03
Italy	Yes	672	21	19.85	5.39	28.22	24.19
Netherlands	Yes	352	11	23.39	5.44	17.41	17.23
Portugal	Yes	160	5	10.52	3.59	45.12	23.82
Spain	Yes	544	17	15.43	4.02	23.27	18.46
Sweden	No	256	8	22.62	5.47	12.20	21.74
United Kingdom	No	1152	36	20.47	9.06	35.70	42.22

Notes: The sample includes the EU member states as of 2003, i.e. the EU-15 without Luxembourg. CV $\equiv$ coefficient of variation of log income per capita across regions within the respective country.

It reveals that a country's size does not always coincide with the number of regions. For example, although Germany is much larger than the UK with respect to area and population, the UK has more NUTS-2 regions. This is because the NUTS segmentation is based on an administrative and not a functional classification. For reasons of data availability we use NUTS-2 data.

The two columns on the right of Table 6.2 report the coefficient of variation (CV) for the start and end of the period. CV is a measure of income dispersion among NUTS-2 regions within a country. Since the CVs are normalized values, they can be directly compared across regions and over time. Thus, a CV that decreases over time is equivalent to σ convergence within a country. Table 6.2 reveals that CVs decrease for seven out of 14 countries over time, which indicates the presence of σ convergence within these countries. Interestingly, all GIPS countries experienced a substantial decrease in CVs, whereas core European countries such as Germany, France, the Netherlands, and Denmark have quite stable CVs. Conversely, Sweden and Finland have a strongly increasing income variation over the sample period. However, the CVs for some countries have to be treated with caution owing to a low number of NUTS-2 regions, such as the case for Ireland.

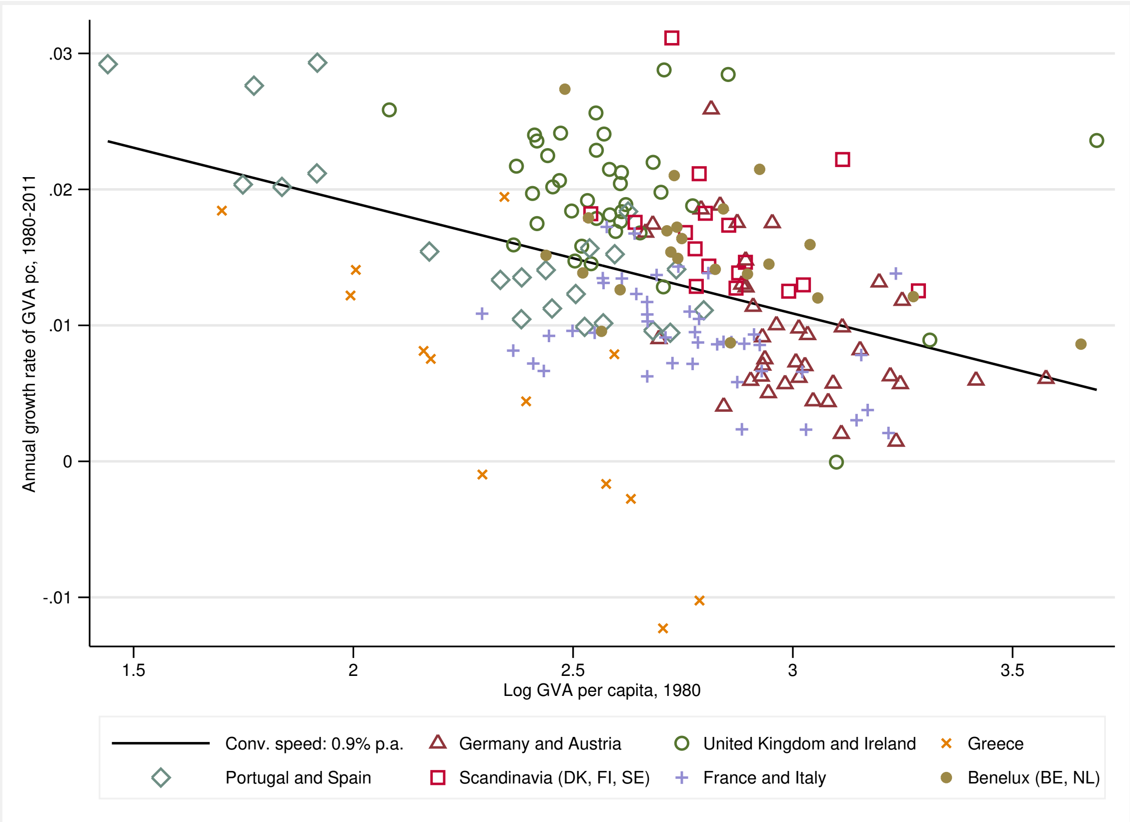

Fig. 6.1: EU-15 panel: β convergence across European regions (scatter plot of initial log GVA per capita and annual growth rate during 1980–2011, $N = 194$).

An alternative way of describing the data in our sample is the scatter plot in Figure 6.1. The slope of the fitted line in Figure 6.1 represents the coefficient of an unconditional β convergence regression. The estimated coefficient is statistically significant and yields a convergence speed of $\hat{\beta} = .009$ (0.9%). This is considerably smaller than existing empirical evidence on unconditional convergence processes, with rates close to 2% per annum reported (Abreu et al., 2005). However, it is evident from Figure 6.1 that fitting lines for regions in certain countries or country groups would reveal faster β convergence in the sense of conditional convergence.

The scatter plot also illustrates within-country heterogeneity. For example, log GVA per capita in 1980 and the subsequent growth rate substantially differ within Greece. Furthermore, the scatter plot shows that Greece is a special case in the sense that all of its regions except one lie below the fitted line, indicating that the average growth rates for Greek regions lie below the sample average. By contrast, all of the Scandinavian regions are located above the fitted line. Within countries or country groups, regional log GVA substantially differed in 1980. This was not always accompanied by different subsequent growth rates in the sense of catching up; for example, starting with similar regional output, some Greek regions grew, whereas other shrank on average. However, it is not clear whether these developments are the result of divergence or transitional dynamics. Finally, one outlier can clearly be identified, Inner London, represented by the dot in the upper right corner of Figure 6.1.

6.4 Estimation Results

6.4.1 Convergence Clubs

Since we are interest in long run growth behaviour, we used the Hodrick–Prescott (HP) filter to separate the time series into trend and cyclical components (Hodrick and Prescott, 1997). The smoothing parameter was chosen according to the method proposed by Ravn and Uhlig (2002), such that the rescaled value for the smoothing parameter is 6.25. Only the trend component was used when applying the log t test. As discussed by Phillips and Sul (2007), the HP filter is common in this type of work.

The log t test applied to the whole panel suggests that the null hypothesis of overall convergence is rejected at the 1% significance level (-2.326). Thus, we performed the PS club clustering procedure.[4] Table 6.3 reports summary results for the club clustering algorithm.

Four clubs can be identified, with a fairly large difference with respect to the end-of-period average income (last column). Moreover, we find one diverging region (Inner London). The club merging algorithm and the merging algorithm for diverging regions do not lead to any amalgamation of clubs or regions, so Table 6.3 shows the final club classification. However,

[4] We thank Monika Bartkowska and Aleksandra Riedl for kindly providing us with their Matlab code for the PS procedure.

Table 6.3: Results of the log t test, 1980-2011

Club	regions	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg inc 1980	avg inc 2011
1	28	0.097 (0.034)	2.862	0.048	18.915	35.840
2	46	0.419 (0.052)	8.074	0.209	15.516	27.329
3	98	-0.027 (0.029)	-0.907	-0.013	15.157	22.419
4	21	0.411 (0.026)	15.972	0.205	9.453	13.479

Notes: Applied truncation parameter: r=0.3; applied critical value: c=0.3; t-statistic at the 5% significance level: -1.645; $\hat{\alpha}$: speed of convergence; number of diverging regions: 1 (Inner London).

both newly proposed algorithms are applied and refine the results of the robustness tests, as described in Section 6.5. The panel contains one low-income, two medium-income, and one high-income club. The $\hat{b}$ values for Clubs 1, 2, and 4 are neither negative nor greater than 2. This indicates that the members of these clubs neither diverge nor converge to the same level, but converge conditionally and diverge with respect to their income levels. The $\hat{b}$ value for Club 3 is negative, but is not statistically different from zero. Following Phillips and Sul (2009), we take this as evidence that Club 3 is a weaker convergence club compared to the other clubs. The convergence speeds $\hat{\alpha}$ substantially differ across clubs. Regions in Club 1 converge at a rate of 4.8%, whereas the convergence speed in Clubs 2 and 4 is close to 21%. An interpretation of $\hat{\alpha}$ for Club 3 does not apply, since its $\hat{b}$ value lacks statistical significance.

The map in Figure 6.2 illustrates the club clustering results. Geographic effects seem to be very pronounced and point to a North-South division in regional income clubs. Moreover, the highly significant Moran's I statistic of the club variable for several distance bands indicate that the clustering has also been influenced by spatial effects. We take this as evidence that the factorization done in the PS procedure is indeed capable of capturing a variety of effects, including spatial ones.

Club 1 contains many cities and metropolitan areas, including Vienna, Salzburg, Brussels, Munich, Hamburg, Frankfurt, Copenhagen, Helsinki, Paris, Dublin, Groningen, Utrecht, Amsterdam, Stockholm, Bristol, Edinburgh, Aberdeen, and the regions west of London. All remaining regions in this club (seven in total) border on these (capital) cities (except the Finish Aland islands and Cheshire, although the latter is adjacent to Manchester and Liverpool).

Club 2 has a more scattered geographic distribution. On the one hand, around two-thirds of the Scandinavian regions are part of it. On the other hand, nearly half of the regions in the UK belong to this club. Larger cities in the south (Madrid, Bilbao, Athens) and wealthier regions and cities in Central Europe (parts of Austria, Belgium, Germany, and the Netherlands) complete the club.

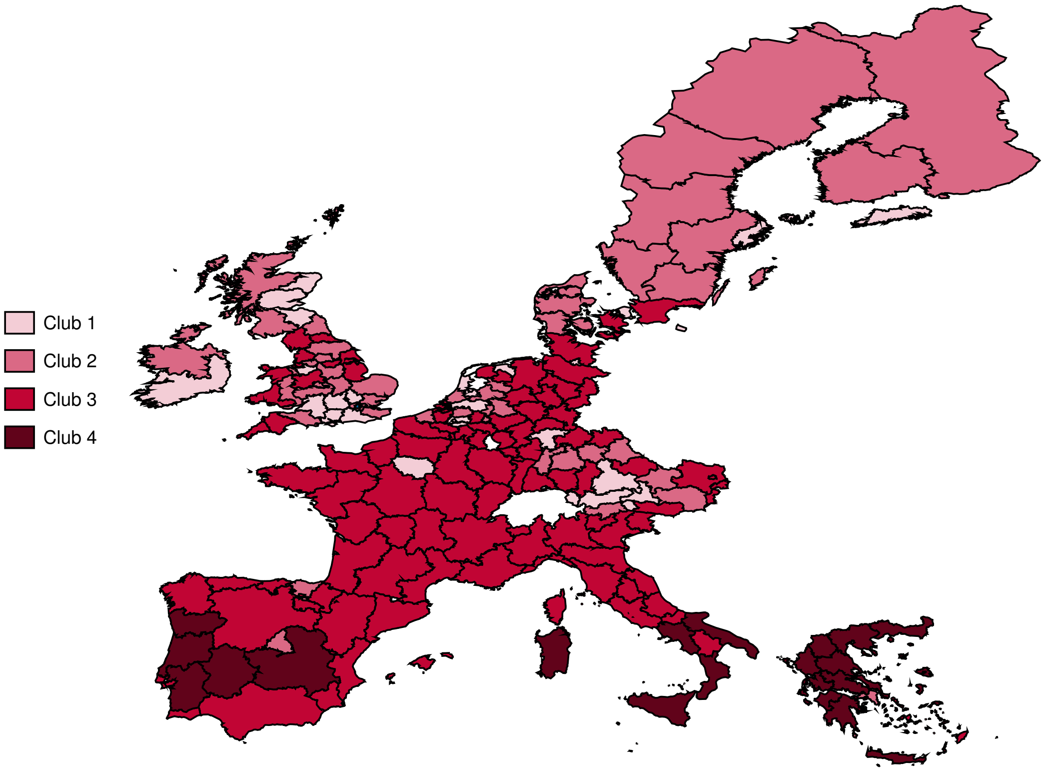

Fig. 6.2: EU-15 panel: club clustering (1980–2011, N=194).

More than half of the sample's regions belong to Club 3, which covers most parts of Central Europe. It contains all of the French regions except Paris, most parts of Belgium and West Germany, northern Italian regions, and coastal areas in Spain. The remaining Austrian, Danish, Dutch, and British regions, as well as Lisbon, the Algarve coast (Portugal), and the southern Aegean islands (Greece) are included. Notably, all regions in Club 4 belong to the so-called GIPS countries. Apart from Greece, for which 85% of all regions fall in Club 4, southern Italy and remaining regions in Portugal and Spain are also included.

Some remarks with respect to the UK and Ireland are in order. Regions in both countries are quantitatively fairly evenly distributed among Clubs 1, 2, and 3. In addition, the UK contains the only diverging region (Inner London) in the whole sample. We conclude that the UK and Ireland might be treated as special cases, not least because of their insular characteristics. In summary, we identify the following four geographical clubs: (1) Western cities, (2) high-income Northern & Central Europe hotspots, (3) Central Europe, and (4) Southern peripheral Europe.

6.4.2 Transitional Behavior

Figure 6.3 shows the relative transition paths for regions within their respective club. The transition path is given by the relative transition coefficient h_{it}, as defined in Eq. (6.2). The graphs show that the transition paths for all clubs clearly form a funnel. The regions in Club 3, which is the largest club with 98 regions, exhibit less strong convergence within their club, as indicated by relatively time-constant transition paths. Furthermore, the transition mostly took place in the period up to 2000, and narrowing of the curves is less evident in the period 2000–2011.

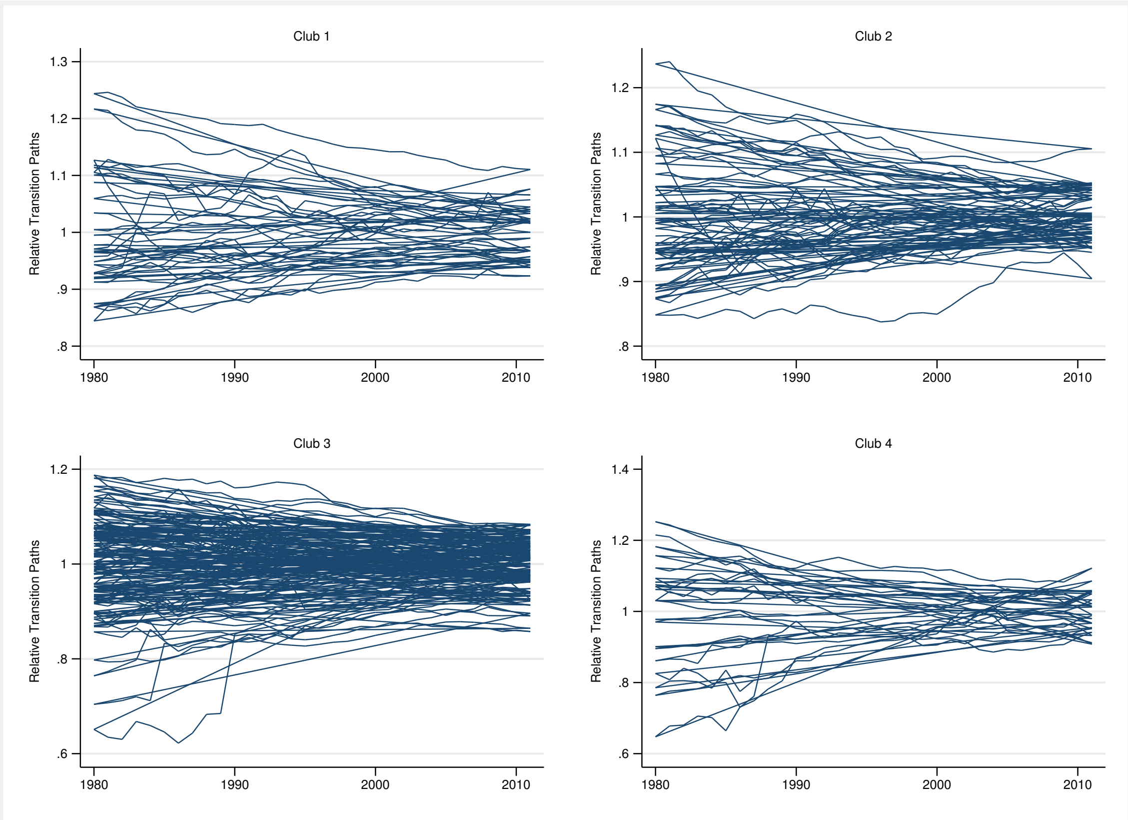

Fig. 6.3: EU-15 panel: relative transition path by club (1980–2011, $N = 194$).

Figure 6.4 illustrates club formation in a scatter plot of log GVA per capita in 1980 versus log GVA per capita in 2011. The distance between each data point and the 45 degree line illustrates the average growth rate over the period. Not surprisingly, the different clubs are vertically staggered according to their income; regions belonging to higher-income clubs had higher growth rates on average. Moreover, growth rates within the clubs are higher for regions that were comparatively poor in 1980. Both findings indicate the presence of catch-up effects and conditional convergence in the sense that regions converge to different steady

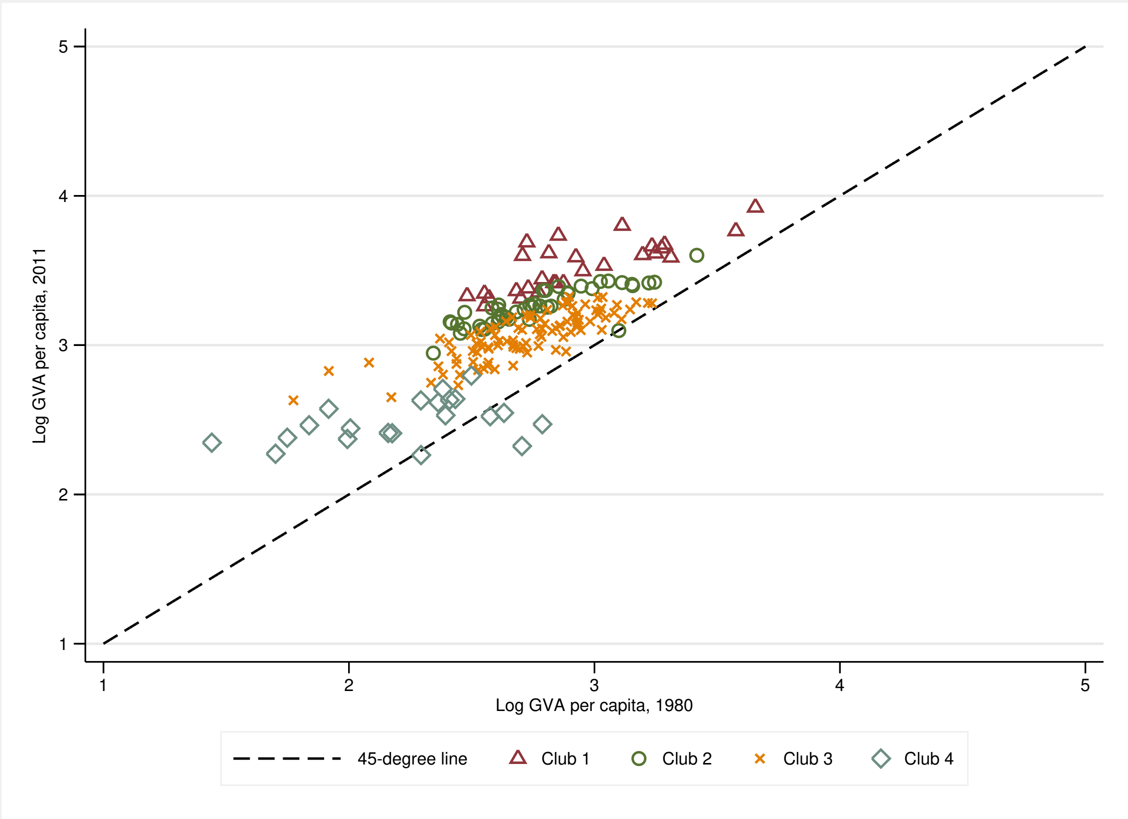

Fig. 6.4: EU-15 panel: scatter plot of club formation (1980–2011, $N = 194$).

states. The graph also reveals a horizontal order of clubs. The lower the income in 1980, the lower the income club on average. This might be a first indication of the club convergence hypothesis. Finally, Figure 6.4 similarly illustrates the within-club convergence process seen in Figure 6.3. Income dispersion within each club is constantly higher in 1980 than in 2011 (e.g., log GVA per capita for Club 2 lies between 2.4 and 3.5 in 1980, but narrowed to the range 2.9–3.6 in 2011).

6.4.3 Convergence Factor Testing

We now discuss results for the ordered logit model introduced in Section 6.3.5. The marginal probabilities for the model are shown in Table 6.4. The sample consists of 193 NUTS-2 regions (without Inner London, which is a diverging region). An overview of the variables and sources used in the ordered logit model is provided in Table 6.9. The summary statistics in Table 6.10 show that the average region has a log income of 2.71 euro and a labor force participation rate of 45 percentage points. The dependent variable is the categorical variable ‘Club membership’, which varies from 1 to 4 with an average value of 2.58 and a median of 3, since Club 3 is the largest club.

Overall, the pattern for the results suggests that initial income per capita and initial human capital, measured in years of schooling, are the most important drivers of club membership. The interpretation is that a one-unit higher log initial income in 1980 increases a region's probability of belonging to Club 1 by 26.6% (Column 1). A one-year increase in average schooling duration increases the probability of belonging to Club 1 by 9.9% and decreases the probability of belonging to Club 4 by 3.9%. With respect to structural characteristics, there is a statistically significant effect of industry and of service share on club membership. A one-unit increase in the initial industry or service share is associated with a higher probability of belonging to Club 1 or 2, and a lower probability of belonging to the lower-income clubs.

The sign of the marginal effect of initial physical capital seems peculiar, since it implies that a one-unit increase in the 1980 per capita gross fixed capital formation decreases the probability of belonging to the higher income Clubs 1 or 2. A closer look shows that this result is driven by the British regions, because of the low physical capital endowment of high-income regions.[5] If the ordered logit procedure is conducted without British regions, the sign of the physical capital variable becomes positive for Club 1 and 2 and negative for Club 3 and 4. A further analysis of this feature is beyond the scope of this paper. It should, however, be addressed by future research, perhaps under consideration of the agglomeration effects brought on by Great Britain's structural transformation from a production-based economy to a system dominated by the service and finance sectors. The results are mostly in line with Bartkowska and Riedl (2012), who find coefficients similar in size but less pronounced in terms of statistical significance. In summary, the findings in Table 6.4 confirm that the initial conditions are relevant in explaining club membership and that log income is the most dominant driver of club membership.

The results in Section 6.4 (with a visual map in Figure 6.2) suggest that geographic factors might play a role in determining the club membership of a region. Hence, we added latitude, a dummy (= 1) indicating if the capital city is located in a region, and a dummy (= 1) for metropolitan areas to the ordered logit model (Table 6.12). Except for minor deviations, the coefficients for the baseline model are robust to the inclusion of geographic variables. The main insight is that latitude and the capital dummy are statistically significant drivers of club membership. The highly significant coefficient for latitude confirms the previously described north–south division within Europe; in other words, the probability of belonging to a higher-income club increases with northerly latitude for a region. The coefficient for the capital dummy suggests that the probability of belonging to Club 1 is 19% higher for regions that include the capital city.

[5] In fact, the average physical capital formation of British regions in 1980 was on average higher in lower income clubs, contrary to to the capital formation of all other regions (cp. Table 6.11).

Table 6.4: Marginal effects on probabilities (ordered logit)

	Club1	Club2	Club3	Club4
Initial conditions (in 1980)				
log income p.c.	0.266**	0.106**	-0.265**	-0.106**
	(4.54)	(2.86)	(-4.82)	(-4.60)
labor force part. rate	0.008**	0.003**	-0.008**	-0.003**
	(2.83)	(2.17)	(-2.84)	(-2.82)
physical capital p.c.	-0.019**	-0.008*	0.019**	0.008**
	(-2.08)	(-1.65)	(2.03)	(2.01)
human capital	0.099**	0.039**	-0.098**	-0.039**
	(5.94)	(3.01)	(-6.18)	(-6.08)
Structural characteristics				
agriculture share	-0.003	-0.001	0.003	0.001
	(-0.16)	(-0.16)	(0.16)	(0.17)
industry share	0.051**	0.020**	-0.051**	-0.020**
	(2.67)	(3.07)	(-3.28)	(-2.71)
service share	0.049**	0.019**	-0.049**	-0.019**
	(2.74)	(3.09)	(-3.36)	(-2.79)
population growth rate	0.075**	0.030	-0.075*	-0.030**
	(1.99)	(1.58)	(-1.87)	(-2.07)
Geographic controls				
population density	-0.003	-0.001	0.003	0.001
	(-0.08)	(-0.08)	(0.08)	(0.08)
No. of observations	193	193	193	193

Notes: McFadden's R^2: 0.438. t-statistics in parentheses, White heteroskedasticity-robust standard errors. **p<0.05,*p<0.1. Data source: CED.

It is important to note that geographic variables in the ordered logit regression serve as control variables which consider geography-related institutional differences. They do not measure the degree of spatial interaction and mutual dependencies between regions, as done by spatial Durbin or a spatial autoregressive models. Nevertheless, spatial effects are not neglected in our analysis, as already mentioned above; the factor representation of the preceding PS methodology implicitly incorporates any effect or influence, also spatial ones, although it does not explicitly measures them. An explicit analysis of possible spatial relationships (Ertur et al., 2006; Basile, 2008) is beyond the scope of this paper.

6.5 Robustness

Robustness checks of the PS procedure can involve the robustness of the club number and composition, and the robustness of the parameter estimates. We checked for both types of robustness using the following twists in our estimation: (1) variation in the time period and the truncation parameter, (2) variation in the level of significance, and (3) estimation for a eurozone panel.

To verify whether the global financial crisis from 2008 onwards had an effect on club formation, we use a panel over the period 1980–2007. The PS procedure leads to the formation of eight clubs. However, our club merging algorithm as described in Sections 6.3.3 decreases the number of clubs to four. Summary results are provided in Table 6.5.

Table 6.5: Results of the log t test, 1980-2007

Club	regions	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg inc 1980	avg inc 2007
1	15	0.285 (0.059)	4.850	0.143	21.145	37.395
2	43	0.265 (0.035)	7.651	0.132	15.627	27.394
3	109	-0.034 (0.035)	-0.944	-0.017	15.394	22.233
4	26	0.042 (0.039)	1.082	0.021	10.004	13.784

Notes: Applied truncation parameter: r=0.3; applied critical value: c=0.3; t-statistic at the 5% significance level: -1.645; $\hat{\alpha}$: speed of convergence; number of diverging regions: 1 (Inner London).
The Phillips and Sul (2007) club clustering algorithm initially detected 8 clubs. By use of our proposed club merging algorithm we could scale down the number of clubs to 4. To assess the ceteris paribus effect of the panel shortening, the last observation ordering of the 1980–2011 panel was kept.

Compared to our baseline results, exclusion of the crisis years does not substantially change the average income structure across both panels. However, the club composition changes slightly, as summarized in Table 6.6.

Table 6.6: Stability of club composition: change in length of panel

Club	baseline panel	shorter panel, 1980-2007				
	club size	club size	change in club size	change in club size	membership stability	regions off to higher/lower club
1	28	15	-13	-46%	54%	-/13
2	46	43	-3	-7%	65%	0/16
3	98	109	11	11%	95%	0/5
4	21	26	5	24%	100%	0/-

Notes: membership stability: percentage of regions which stay in their club when the panel length is shortened to the years 1980 to 2007. Inner London is in both cases the only diverging region.

Three points are noteworthy. First, the stability of the initial club membership is quite pronounced for the two lower-income clubs. For example, 95% of regions belonging to Club 3 in the longer panel belong to the same club for the shorter panel. This does not hold for Club 1, which loses nearly half of its regions to Club 2. Second, changes in club membership on panel shortening only occur in one direction, towards lower-income clubs. This is directly linked to the third point: the two higher-income clubs shrink and the two lower-income clubs gain in overall club size. Whether the crisis itself caused the higher-income clubs to increase in size is a question for further research.

The convergence speed within clubs substantially changes across both panels (although in both panels we estimate a negative and insignificant t value for Club 3). For example, although Club 4 only gains five more regions when clustering the shorter panel (with all the 'old' members remaining in the club), the convergence speed decreases from 20.5% to 2.1%. The test statistic $t_{\hat{b}}$ also decreases from 15.9 to 1.1, and hence becomes nonsignificant. We take this as evidence that the convergence speed must be interpreted with caution. The reason is that inclusion of further regions in a certain club might be justified by the log t test, but might worsen the test statistic and thus the parameter estimates to such an extent that inference is no longer valid. Further research could try to improve the clustering algorithm by excluding the possibility of relatively high jumps in the test statistic.

We apply the PS procedure to two shorter versions of our initial panel. The first covers the period 1990–2011, which excludes all observations before the fall of the Iron Curtain. After use of the proposed club and diverging regions' merging algorithms (Sections 6.3.3 and 6.3.4) the final number of clubs decreases to seven and the number of diverging regions to one. The second panel covers 1990–2007, so data during both the Cold War and the global financial crisis are dropped. After running all three algorithms, we detect eight clubs and one diverging region. For both time spans, the parameter estimates for four clubs are not significantly different from zero, thereby pointing to weaker convergence clubs. Summary results for both panels are provided in the Appendix (Tables 6.13 and 6.14). We take the results for both subpanels as an indication of the rapid increase in discriminatory power of the log t test as the sample size decreases.

Besides changing the input panel, we also change the truncation parameter r in the log t test. Phillips and Sul (2007) propose $r = 0.3$, which we used in all our previous regressions. To check for robustness, we use $r = 0.2$ and $r = 0.4$. For $r = 0.2$, we estimate five clubs, with a clustering pattern quite different to the pattern of our baseline results (Table 6.15). For $r = 0.4$, the algorithm generates four clubs with remarkable size and composition similarities to our baseline clubs (Tables 6.16 and 6.17). The convergence speed is close to the baseline result for Clubs 1 and 2, but sharply differs for Clubs 3 and 4.

We also test for robustness with respect to the level of significance. It should be noted that the PS procedure does not use the significance level as a post-estimation measure to classify the validity of a result. Instead, the significance level is used in the clustering algorithm to increase or decrease the discriminatory power of the procedure. The higher the significance level, the higher is the discriminatory power of the algorithm in the sense that membership of a certain existing club becomes less likely for a certain region. Accordingly, use of a low significance level usually leads to detection of fewer clubs.

Besides our baseline value of 5%, we apply significance levels of 0.1%, 1%, 10%, and 25%. The results do not change, except for the 25% level; in this case, the size and parameters of Clubs 2–4 alter, as illustrated in Table 6.7.[6] Interestingly, the size of the two medium-income clubs nearly balances. Although Club 2 increases by 25 regions, its speed of convergence remains stable at 21%. Club 3 now has a positive and significant speed of convergence of 7%. However, the parameter estimate for Club 4 becomes nonsignificant, pointing to a weaker convergence club.

Table 6.7: Results of the log t test, 1980-2011, sign.level=25%

Club	regions	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg inc 1980	avg inc 2011
1	28	0.097 (0.034)	2.862	0.048	18.915	35.840
2	71	0.419 (0.049)	8.504	0.210	15.720	26.620
3	68	0.134 (0.046)	2.914	0.067	14.923	21.661
4	26	0.020 (0.036)	0.543	0.010	10.260	14.394

Notes: Applied truncation parameter: r=0.3; applied critical value: c=0.3; t-statistic at the 25% significance level: -0.674; $\hat{\alpha}$: speed of convergence; number of diverging regions: 1 (Inner London).

The Phillips and Sul (2007) club clustering algorithm initially detected 5 clubs and 3 diverging regions. By use of our proposed club merging and diverging regions merging algorithms we could scale down the number of clubs to 4 and the number of diverging regions to 1.

Finally, we calculate estimates for a eurozone panel containing 145 NUTS-2 regions for the same time span (1980–2011). When applying the PS club clustering algorithm we have to increase the critical value to $c = 2.7$. Table 6.8 summarizes the clustering algorithm results.[7]

Table 6.8: Results of the log t test, 1980-2011, eurozone panel

Club	regions	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg inc 1980	avg inc 2011
1	24	0.025 (0.037)	0.686	0.013	20.028	35.068
2	64	0.297 (0.061)	4.840	0.148	16.751	24.953
3	30	0.239 (0.048)	5.035	0.120	14.099	20.128
4	27	-0.011 (0.045)	-0.232	-0.005	10.512	14.627

Notes: Applied truncation parameter: r=0.3; applied critical value: c=2.7; t-statistic at the 5% significance level: -1.645; $\hat{\alpha}$: speed of convergence; number of diverging regions: 1 (Brussels).

The Phillips and Sul (2007) club clustering algorithm initially detected 6 clubs and 2 diverging regions. By use of our proposed club merging and diverging regions merging algorithms we could scale down the number of clubs to 4 and the number of diverging regions to 0.

In the eurozone case, four clubs are eventually detected. The clubs with the lowest and highest income are quite stable in size, membership, and average income compared to the baseline estimation. Nevertheless, both clubs are classified as weak owing to their

[6] Table 6.18 summarizes the club composition stability.
[7] Table 6.19 summarizes the club composition stability.

nonsignificant $\hat{b}$ coefficients. Moreover, a majority of regions clustered in Club 3 in the EU panel enter Club 2 in the eurozone panel, accompanied by a substantial change in parameter estimates.

Overall, this section illustrates that the number of clubs is very stable across different panel specifications. The same largely holds for size, average income, and membership stability of the lowest-income club. There is, however, much volatility among coefficients for the remaining clubs. Future research could investigate whether these differences are associated with major political or economic shocks, or whether the methodology applied is appropriate for identifying the speed of convergence. In this respect, the PS clustering algorithm could be refined to take into account the relative effect of single regions joining a core group or a club.

6.6 Discussion and Conclusion

We investigated the presence of club convergence in income per capita for NUTS-2 regions in Europe. To this end, we adopted a nonlinear time-varying factor model and the log t test proposed by Phillips and Sul (2007). The PS model tests whether the transition coefficient δ_{it}, which measures distance to a common growth path μ_t, converges towards the panel average δ as $t \to \infty$. Thus, in contrast to previous methods, the PS approach allows for transitional heterogeneity and divergence from the actual growth path.

We also applied the PS club clustering algorithm, which groups individual regions in certain convergence clubs according to the log t test. We augmented the existing methodology with two post-clustering algorithms of particular interest for wider and/or shorter samples when the PS club clustering algorithm leads to a comparatively large number of convergence clubs and diverging regions. Our estimation results in Section 6.5 show that both algorithms have an impact and finalize club formation. After identifying convergence clubs purely based on income per capita, we tested further explanatory convergence factors using an ordered response model. The underlying questions are whether initial or structural conditions determine a region's membership in a given club.

Our main result is the identification of four convergence clubs along geographic lines: (1) Western cities, (2) high-income Northern & Central Europe hotspots, (3) Central Europe, and (4) southern peripheral Europe. The number of income clubs is robust for various specifications of the baseline model. However, the variation of coefficients in the robustness tests indicates that the PS club clustering procedure might need some refinements. In particular, researchers should ensure that inclusion of a certain region in an existing club does not substantially change the club transition coefficients.

Application of the ordered logit model corroborates the club convergence hypothesis in the sense that the initial conditions play a role in club membership. The probability of belonging to one of the two higher-income clubs increases with the initial labor force participation rate, the initial human capital, and the log initial income per capita. Extension of the ordered logit model using geographic variables confirms the conjecture of strong positive metropolitan effects and a north-to-south decline in income.

These results differ in part from findings in empirical studies using the PS procedure. Bartkowska and Riedl (2012), whose testing agenda we partly follow, use income per worker data in 206 NUTS-2 regions of the EU-15 over the period 1990–2002. They identify six convergence clubs, although these are geographically scattered. We suspect that use of per-worker values has a cushioning effect such that clustering is less pronounced. Moreover, our robustness tests revealed that the number of clubs increases if panels become too short. This might explain the higher number of clubs detected by Bartkowska and Riedl (2012) in their comparatively short panel. Based on NUTS-2 data, we find robust results in favour of four convergence clubs and a clear geographic pattern. By contrast, Monfort et al. (2013) and Apergis et al. (2010), who use national data over a time span similar to ours, find only one and two convergence clubs.

Our results suggest that club convergence holds within the EU, indicating a multi-speed Europe along geographic lines. Income growth paths differ substantially among Northern, Central, and Southern Europe. Although overall income convergence does not hold, European regional policy has not necessarily failed. On the one hand, policy measures need time to make a measurable impact. On the other hand, even perfectly equalized opportunities are likely to lead to region-specific growth paths if different initial conditions matter or if differences in region-specific structural characteristics prevail. In these cases, all efforts to achieve absolute income convergence have a natural limit. In light of a multi-speed Europe, the policy question is what income differences European citizens are willing to accept. Given our results European regional and structural policy should strive to support regions in converging within their respective income club for the time being.

There are several directions for further research. The PS log t test can be applied to data sets not yet considered, such as NUTS-1 data. In this respect, the question of the most suitable level of investigation is not fully answered. Comparison of results between national and NUTS-1, -2, and -3 data for the same area over the same period might be a first step in answering this question. From a methodological perspective, improvement, simplification, or merger of the three algorithms used in this study might be of interest. Finally, the stagnating income transition within clubs from 2000 onwards (Figure 6.3) calls for a thorough investigation.

6.7 Appendix

Table 6.9: Variables and sources

Variable	Definition	Availability	Source
Log income p.c.	Gross Value Added (GVA) divided by total population (2005 const. prices)	1980-2011	CED
Physical capital	Gross Fixed Capital Formation divided by total population (2005 const. prices)	1980	CED
Human capital	Average Years of Schooling Attained	1980	B&L
Labor force participation rate	Active population as share of total population	1980-2011	CED
Agriculture	GVA in agricultural sector as a share of total GVA	1980-2011	CED
Industry	GVA in manufacturing, energy & construction sector as a share of total GVA	1980-2011	CED
Services	GVA in service sector as a share of total GVA	1980-2011	CED
Population	Number of permanent residents of respective region	1980-2011	CED
Area	Area in square kilometer		Eurostat
Latitude	Regions' weighted average latitude		ETIS
Capital	Respective region comprises the country's capital city		CED
Metropolitan area	Region neighbouring a capital region		CED

Notes: CED: Cambridge Econometrics Database. B&L: Barro and Lee (2013). ETIS: European Transport Policy Information System.

Table 6.10: Summary statistics

	mean	median	s.d.	min	max
Club membership	2.580	3	0.869	1	4
Log income p.c.	2.710	2.722	0.333	1.441	3.656
Labor force participation rate	0.453	0.447	0.073	0.281	0.661
Physical capital p.c.	3.467	3.439	1.768	0.198	17.11
Human capital	7.489	7.101	1.162	4.649	9.856
Agriculture share	0.028	0.019	0.03	0	0.169
Industry share	0.284	0.287	0.072	0.106	0.513
Service share	0.680	0.674	0.082	0.421	0.899
Population growth rate	0.817	0.767	0.593	-0.92	3.055
Population density	0.162	0.069	0.322	0.001	2.562

Table 6.11: Average p.c. gross fixed capital formation in 1980 (in Euro)

	Club 1	Club 2	Club 3	Club 4
all regions	3668	3270	3711	2490
British regions	1220	2248	3922	NA
non-British regions	4647	3815	3684	2490

Table 6.12: Robustness: marginal effects on probabilities (ordered logit) with geographic controls

	Club1	Club2	Club3	Club4
Initial conditions (in 1980)				
	b/t	b/t	b/t	b/t
log income p.c.	0.185**	0.112**	-0.224**	-0.073**
	(3.04)	(2.95)	(-3.50)	(-3.43)
labor force part. rate	0.006**	0.004**	-0.008**	-0.003**
	(2.49)	(2.33)	(-2.67)	(-2.60)
physical capital p.c.	-0.016*	-0.009	0.019*	0.006*
	(-1.88)	(-1.63)	(1.88)	(1.81)
human capital	0.065**	0.039**	-0.078**	-0.025**
	(3.09)	(3.13)	(-3.71)	(-3.46)
Structural characteristics				
agriculture share	-0.013	-0.008	0.016	0.005
	(-0.93)	(-0.88)	(0.91)	(0.94)
industry share	0.035**	0.021**	-0.042**	-0.014**
	(2.13)	(2.45)	(-2.45)	(-2.32)
service share	0.032**	0.019**	-0.039**	-0.013**
	(2.13)	(2.49)	(-2.46)	(-2.33)
population growth rate	0.085**	0.051**	-0.102**	-0.033**
	(2.56)	(2.19)	(-2.58)	(-2.77)
Geographic controls				
population density	-0.025	-0.015	0.030	0.010
	(-0.49)	(-0.52)	(0.50)	(0.50)
latitude	0.011**	0.006*	-0.013**	-0.004**
	(2.48)	(1.84)	(-2.31)	(-2.39)
capital	0.189**	0.114**	-0.228**	-0.074**
	(3.17)	(2.09)	(-2.94)	(-2.75)
metropolitan area	0.038	0.023	-0.046	-0.015
	(1.09)	(1.01)	(-1.08)	(-1.07)
No. of observations	193	193	193	193

Notes: McFadden's R^2: 0.472. t-statistics in parentheses, White heteroskedasticity-robust standard errors. **p<0.05,*p<0.1. Data source: CED, ETIS.

Table 6.13: Results of the log t test, 1990-2011

Club	regions	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg inc 1990	avg inc 2011
1	13	0.184 (0.066)	2.773	0.092	28.506	41.166
2	8	0.090 (0.051)	1.762	0.045	22.083	32.681
3	48	0.034 (0.048)	0.701	0.017	19.936	28.391
4	61	0.209 (0.072)	2.903	0.105	17.915	23.944
5	34	0.109 (0.092)	1.187	0.055	16.478	20.640
6	11	0.192 (0.084)	2.291	0.096	12.770	16.569
7	18	0.006 (0.048)	0.124	0.003	10.600	13.152

Notes: Applied truncation parameter: r=0.3; applied critical value: c=0.3; t-statistic at the 5% significance level: -1.645; $\hat{\alpha}$: speed of convergence; number of diverging regions: 1 (Inner London).

The Phillips and Sul (2007) club clustering algorithm initially detected 8 clubs and 4 diverging regions. By use of our proposed club merging and diverging regions merging algorithms we could scale down the number of clubs to 7 and the number of diverging regions to 1.

Table 6.14: Results of the log t test, 1990-2007

Club	regions	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg inc 1990	avg inc 2007
1	13	-0.012 (0.075)	-0.158	-0.006	28.506	38.898
2	29	0.108 (0.047)	2.319	0.054	22.178	29.437
3	38	0.195 (0.059)	3.331	0.098	19.011	25.207
4	59	0.058 (0.060)	0.968	0.029	17.642	22.435
5	21	0.175 (0.108)	1.620	0.087	15.623	19.354
6	14	0.034 (0.084)	0.404	0.017	13.131	16.476
7	16	0.206 (0.088)	2.344	0.103	10.702	13.138
8	3	2.045 (0.074)	27.574	1.022	9.452	10.791

Notes: Applied truncation parameter: r=0.3; applied critical value: c=0.3; t-statistic at the 5% significance level: -1.645; $\hat{\alpha}$: speed of convergence; number of diverging regions: 1 (Inner London).

The Phillips and Sul (2007) club clustering algorithm initially detected 16 clubs and 4 diverging regions. By use of our proposed club merging and diverging regions merging algorithms we could scale down the number of clubs to 8 and the number of diverging regions to 1.

To assess the ceteris paribus effect of the panel shortening, the last observation ordering of the 1980–2011 panel was kept.

Table 6.15: Results of the log t test, 1980-2011, $r = 0.2$

Club	regions	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg inc 1980	avg inc 2011
1	14	0.318 (0.078)	4.091	0.159	21.641	40.240
2	53	0.299 (0.049)	6.143	0.149	16.368	28.920
3	63	0.351 (0.088)	3.966	0.175	15.391	24.205
4	39	0.125 (0.066)	1.900	0.062	13.893	19.973
5	24	-0.048 (0.042)	-1.133	-0.024	10.219	14.200

Notes: Applied truncation parameter: r=0.2; applied critical value: c=0.3; t-statistic at the 5% significance level: -1.645; $\hat{\alpha}$: speed of convergence; number of diverging regions: 1 (Inner London).

The Phillips and Sul (2007) club clustering algorithm initially detected 8 clubs and 1 diverging region. By use of our proposed club merging algorithm we could scale down the number of clubs to 5.

Table 6.16: Results of the log t test, 1980-2011, $r = 0.4$

Club	regions	$\hat{b}$ (s.e.)	$t_{\hat{b}}$	$\hat{\alpha}$	avg inc 1980	avg inc 2011
1	38	0.061 (0.018)	3.447	0.031	18.117	34.035
2	49	0.452 (0.038)	11.969	0.226	14.932	26.155
3	78	0.179 (0.042)	4.242	0.089	15.525	22.475
4	28	0.053 (0.035)	1.511	0.026	10.576	14.743

Notes: Applied truncation parameter: r=0.4; applied critical value: c=0.3; t-statistic at the 5% significance level: -1.645; $\hat{\alpha}$: speed of convergence; number of diverging regions: 1 (Inner London).

Table 6.17: Stability of club composition: change in the truncation parameter

Club	baseline panel	shorter panel, $r = 0.4$				
	club size	club size	change in club size	change in club size	membership stability	regions off to higher/lower club
1	28	38	10	36%	100%	-/0
2	46	49	3	7%	78%	10/0
3	98	78	-20	-20%	80%	13/7
4	21	28	7	33%	100%	0/-

Notes: membership stability: percentage of regions which stay in their club when the truncation parameter is increased from $r = 0.3$ to $r = 0.4$. Inner London is in both cases the only diverging region.

Table 6.18: Stability of club composition: change in the significance level

Club	baseline panel	Significance level: 25%				
	club size	club size	change in club size	change in club size	membership stability	regions off to higher/lower club
1	28	28	0	0%	100%	-/0
2	46	71	25	54%	100%	0/0
3	98	68	-30	-31%	69%	25/5
4	21	26	5	24%	100%	0/-

Notes: membership stability: percentage of regions which stay in their club when the significance level is increased from 5% to 25%. Inner London is in both cases the only diverging region.

Table 6.19: Stability of club composition: eurozone panel

Club	baseline panel	Euro Zone Panel				
	club size	club size	change in club size	change in club size	membership stability	regions off to higher/lower club
1	18	24	6	25%	100%	-/0
2	21	64	43	205%	71%	6/0
3	85	30	-55	-65%	35%	49/6
4	21	27	6	29%	100%	0/-

Notes: The baseline clubs are reduced by regions which are not members of the Euro zone. Membership stability: percentage of regions which are in the same club when an Euro Zone panel is estimated. Brussels is the only diverging region in the Euro Zone panel.

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Summary

This dissertation has a twofold agenda: first, macroeconomic imbalances within the Eurozone are assessed from a theoretical perspective; secondly, regional per capita income growth patterns within the EU are investigated using empirical methods.

Chapter 2–3 examine the effect of a negative real interest rate shock on macroeconomic variables, in particular on the current and capital accounts. In Chapter 2 it is argued that the allocation mechanism for interest-bearing capital in a monetary union differs from that in a regime with monetarily autonomous states. Since the demand for capital is driven by real values and the supply by nominal values (real costs vs. nominal returns), capital does not allocate efficiently. Moreover, given equal nominal interest rates across a monetary union, capital demand is the only effective driver of allocation and causes self-enforcing, pro-cyclical, and ultimately inefficient flows. Chapter 3 illustrates how in light of a demand-driven capital allocation a negative real interest rate shock affects various macroeconomic variables. The incorporation of a microeconomic model into a system of income accounting reveals that various developments observable in the Eurozone can be explained by a real interest rate shock on a static system, thereby questioning the assertion that irresponsible behavioral changes have caused the emergence of macroeconomic imbalances.

Chapter 4–6 investigate regional per capita income growth patterns within the European Union and examine whether the observed clusters can be explained by the club convergence hypothesis. In this respect, Chapter 4 provides a methodological contribution. Monte Carlo simulations are employed to assess the improvement in clustering precision if the Phillips and Sul (2007) clustering algorithm is followed by a club merging algorithm instead of a club merging rule (Phillips and Sul, 2009). Moreover, this extended clustering procedure is compared to a novel hierarchical clustering algorithm. Results reveal that both new methods considerably improve the precision of clustering. In Chapter 5 the previous methods as well as a novel club core identification procedure are applied to a panel of 68 NUTS-1 regions. The study in Chapter 6 extends the Phillips and Sul (2007) algorithm by two post-clustering algorithms and uses these methods and an ordered logit model to assess club convergence in per capital income across 194 NUTS-2 regions. The results in Chapter 5 indicate that heterogeneity across European regions has been growing in the past 13 years, thereby strengthening the importance of the club convergence hypothesis. The latter is explicitly confirmed in Chapter 6.

Overall findings indicate that the European integration process has in parts failed to achieve its own objectives. The key policy challenges are to adjust the pace of integration to its natural limitations and to find a sensitive way to handle a multi-speed Europe.

Zusammenfassung

Die vorliegende Dissertation hat zwei Schwerpunkte: zum einen werden makroökonomische Ungleichgewichte innerhalb der Eurozone aus einer theoretischen Perspektive beleuchtet, zum anderen werden regionale Wachstumsmuster des pro-Kopf Einkommens innerhalb der EU mit Hilfe empirischer Methoden untersucht.

Die Kapitel 2–3 befassen sich mit den Effekten eines negativen Realzins-Schocks auf makroökonomische Variablen, insbesondere auf die Leistungs- und Kapitalbilanz. In Kapitel 2 wird postuliert, dass in einer Währungsunion der Allokationsmechanismus für zinsvergütetes Kapital anderen Gesetzmäßigkeiten unterliegt als in einem Regime mit monetär autonomen Staaten. Da die Kapitalnachfrage von realen, das Kapitalangebot hingegen von nominalen Variablen abhängt (reale Kosten ggü. nominalen Erträgen), ist die Kapitalallokation nicht effizient. Ferner ist in Anbetracht gleicher nominaler Zinsen innerhalb einer Währungsunion nur die Kapitalnachfrage ein wirksamer Allokationstreiber, was zu selbstverstärkenden, prozyklischen und letztlich ineffizienten Kapitalflüssen führt. Kapital 3 veranschaulicht, wie sich im Lichte einer nachfragebedingten Kapitalallokation ein negativer Realzinsschock auf verschiedene makroökonomische Variablen auswirkt. Die Einbettung eines mikroökonomischen Modells in ein System aus Einkommensidentitäten zeigt auf, dass verschiedene Entwicklungen, die in der Eurozone zu beobachten waren, mit einem Realzins-Schock auf ein statisches System erklärt werden können. Dieses Ergebnis stellt die Behauptung, dass verantwortungslose Verhaltensänderungen das Entstehen makroökonomischer Ungleichgewichte verursacht haben, in Frage.

In den Kapiteln 4–6 werden regionale Wachstumsmuster des pro-Kopf Einkommens innerhalb der Europäischen Union untersucht. Ferner wird analysiert, ob die zu beobachtenden Cluster mit Hilfe der Klub-Konvergenz Hypothese erklärt werden können. Zu diesem Zweck liefert Kapitel 4 zunächst einen methodischen Beitrag. Es kommen Monte-Carlo-Simulationen zum Einsatz, um Cluster-Verbesserungen für den Fall zu bewerten, in welchem der Phillips–Sul (2007) Clusteralgorithmus durch einen Klub-Fusionsalgorithmus anstatt durch eine einfache Fusionsregel (Phillips und Sul, 2009) komplementiert wird. Zudem wird diese erweiterte Methode mit einem neuen hierarchischen Clusteralgorithmus verglichen. Die Ergebnisse zeigen, dass beide neu vorgeschlagenen Verfahren die Güte der Clusterbildung erheblich verbessern. In Kapitel 5 kommen die neuen Methoden sowie ein innovatives Verfahren, welches die Kernregionen der Klubs identifiziert, bei der Untersuchung eines 68 NUTS-1-Regionen umfassenden Panels zum Einsatz. Die Studie in Kapitel 6 erweitert den Phillips–Sul (2007)-Clusteralgorithmus um zwei nachgelagerte Algorithmen. Anschließend werden diese Methodik sowie eine logit-Regression angewandt, um zu überprüfen, ob die Entwicklung des Pro-Kopf-Einkommens in 194 NUTS-2-Regionen durch

Klub-Konvergenz bedingt ist. Die Ergebnisse in Kapitel 5 deuten darauf hin, dass die Heterogenität zwischen Europäischen Regionen in den letzten 13 Jahren gewachsen ist. Dieses Ergebnis veranschaulicht die steigende Relevanz der Klub-Konvergenz-Hypothese, die in Kapitel 6 explizit bestätigt werden kann. In der Gesamtschau finden sich Hinweise, dass der Europäische Einigungsprozess in Teilen an seinen eigenen Ansprüchen scheitert. Die sich ergebenden politischen Herausforderungen beinhalten insbesondere eine stärkere Orientierung der Integrationsgeschwindigkeit an den natürlichen Integrationsgrenzen sowie politisch weitsichtiges Handeln in Anbetracht eines Europas der multiplen Geschwindigkeiten.

Veröffentlichungen

Die Studie, auf denen die Kapitel 2 und 3 basieren, wurde auf der 16th EBES Conference in Istanbul (Mai 2015) vorgestellt und ist auf der Proceeding CD veröffentlicht.

Eine frühere Version der Studie in Kapitel 6 wurde auf der 8th RGS Doctoral Conference on Economics (Februar 2015, Universität Duisburg-Essen) vorgestellt. Inzwischen wurde die Studie im Journal *Empirical Economics* online (Juni 2016) und als Printversion (März 2017) publiziert.

Selbstdeklaration

Für die Studien in Kapitel 2 bis Kapitel 5 liegt die jeweilige Eigenleistung

der Konzipierung / Planung bei	100%
der Durchführung bei	100%
der Manuskripterstellung bei	100%

Für die Studie in Kapitel 6 liegt die Eigenleistung

der Konzipierung / Planung bei	50%
der Durchführung bei	50%
der Manuskripterstellung bei	50%

Die vorliegende Einschätzung in Prozent über die von mir erbrachte Eigenleistung wurde mit den am Artikel beteiligten Koautoren einvernehmlich abgestimmt.

Ort/Datum

Unterschrift Doktorand

Erklärung

Hiermit erkläre ich, Konrad Nikolaus Freiherr von Lyncker-Ehrenkrook, dass ich keine kommerzielle Promotionsberatung in Anspruch genommen habe. Die Arbeit wurde nicht schon einmal in einem früheren Promotionsverfahren angenommen oder als ungenügend beurteilt.

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Eidesstattliche Versicherung

Ich, Konrad Nikolaus Freiherr von Lyncker-Ehrenkrook, versichere an Eides statt, dass ich die Dissertation mit dem Titel

Macroeconomic Imbalances in the Process of European Integration: Theoretical Considerations and Empirical Evidence

selbst und bei einer Zusammenarbeit mit anderen Wissenschaftlern gemäß den beigefügten Darlegungen nach § 6 Abs. 3 der Promotionsordnung der Fakultät Wirtschafts- und Sozialwissenschaften vom 24. August 2010 verfasst habe.

Ort/Datum	Unterschrift Doktorand
	Unterschrift Verwaltung

This dissertation attempts to shed light on macroeconomic imbalances and growth divergence across Europe and the eurozone. The agenda is twofold: the first focus is on causes of macroeconomic imbalances from a theoretical perspective; the second focus is on income growth patterns across European regions from an empirical perspective.

The implementation of this agenda is based on five separate studies. Theoretical implications of converging nominal interest rates on macroeconomic variables are addressed in Chapter 2 and Chapter 3. Chapter 4 presents a Monte Carlo study, which evaluates different clustering procedures to detect convergence clubs in panel data. Chapter 5 and Chapter 6 attempt to identify regional convergence clubs in Europe, using panel data on two different levels of aggregation (NUTS-1 and NUTS-2).

Overall findings indicate that the European integration process has in parts failed to achieve its own objectives. The key policy challenges are to adjust the pace of integration to its natural limitations and to find a sensitive way to handle a multi-speed Europe.