# Essays on Empirical Macroeconomics: Convergence and Risk Sharing

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# Preface

This thesis presents the research I undertook during the four years as a research and teaching assistant at the Chair of Macroeconomics at the University of Dortmund. It has been a pleasure to write this thesis under the supervision of Professor Heinz Holländer and Professor Mathias Hoffmann and I am indebted to both of them for their support. In particular, I would like to thank Mathias Hoffmann for his suggestion to develop a transfer of techniques from the growth econometrics literature to the macroeconomic literature on aggregate risk sharing. Both papers presented in Part II pick up this suggestion.

I have highly benefited from discussions with professors, colleagues, and fellow doctoral students of the Graduiertenkolleg 'Allokationstheorie, Wirtschaftspolitik und kollektive Entscheidungen'. Moreover, I have benefited from many comments and suggestions which I have received at various international conferences.

A *very* special mentioning deserves my colleague Christian Bayer. He was a sounding board for new ideas and helped me to improve my research throughout the whole process. The second chapter of this thesis presents a paper which we have written in joint work. A non-exhaustive list of other people that in some way had an impact on the final version includes Michael Roos, Eckhardt Bode, Wolfram Richter, Wolfgang Leininger, Kornelius Kraft, Christoph Alsleben, Julia Angerhausen, Christiane Schuppert, and Frauke Eckermann. Moreover, I thank several anonymous referees of academic journals who have peer-reviewed the papers presented in Sections 2, 3, and 4.

# Chapter 1

# Introduction

This thesis presents an analysis of empirical and policy issues related to economic convergence and risk sharing. While the first part of the thesis is a contribution to the empirical literature on regional convergence, the second part is concerned with a transfer of techniques originally proposed in the growth econometrics literature to the macroeconomic literature on aggregate risk sharing. Taken as a whole, my thesis therefore illustrates how recent advances in growth econometrics are of great service in other areas of economic research.

The thesis consists of four self-contained papers.[1] In this Introduction I put my papers into a larger context. Since the papers cover topics from different areas of economic research—such as labor markets, convergence, and risk sharing—the focus of this Introduction is methodological in nature and economic contributions and possible policy implications are deliberately touched only marginally. These issues are discussed in considerable detail in the respective chapters.

The various empirical applications presented have in common that the attention is restricted to a domestic setting. As discussed by Hess and van Wincoop (2000), the analysis of economic interactions across regions within a country holds great potential for understanding how economic interactions between countries will evolve as national borders decline in importance. There are various reasons why regional (or intranational) studies may provide a proper benchmark for understanding macroeconomic relationships within an economically integrated geographic area:

> 'Policy-imposed barriers to the flow of goods, capital, labor, and knowledge across intranational borders are generally quite small.

[1] The first paper 'Convergence in West German Regional Unemployment Rates' is coauthered by my colleague Christian Bayer.

> Tariffs, trade quotas, capital controls, and immigration laws do not apply to intranational borders. Regions within a country share a common currency, tax system, legal foundations, accounting system, and language' (Hess and van Wincoop, 2000, p. 2).

Regional studies on macroeconomic issues are abundant but most of the literature is still rather separated: some researchers work on growth and convergence, some on labor market issues, some on agglomeration, others on risk sharing, and still others on labor migration. The book of Hess and van Wincoop (2000) illustrates how the various contributions can be unified in a new field, which they refer to as 'Intranational Macroeconomics'. This thesis presents a collection of self-contained papers which contribute to this evolving field of research.

## 1.1 Part I: Regional Convergence in Germany

There is a large body of empirical research on national and regional economic growth and convergence. The question whether economies are converging has attracted the attention of economists and policy makers at least since the last two decades. Almost all studies of convergence refer explicitly or implicitly to variants of the neoclassical model of growth, originally set out by Solow (1956) and Swan (1956), and, following the work of Ramsey (1928), subsequently refined by Cass (1965) and Koopmans (1965).

According to Solowian-type of growth models, convergence is driven by decreasing returns to capital accumulation. This property of the neoclassical production function implies that income differences between independent countries or regions will diminish over time as those countries move to identical steady states.

The broad literature testing whether countries or regions are converging is surveyed, among others, in Temple (1999), Durlauf and Quah (1999), Islam (2003), Magrini (2004), Abreu (2005), and several chapters of the recent Handbook of Economic Growth (Aghion and Durlauf, 2005). Following the classification suggested by Magrini (2004), two broad approaches to analyzing convergence can be identified: the 'regression approach' and the 'distribution dynamics approach'.

Within the regression approach, a variety of methods has been developed and implemented which I summarize in a chronological order. Starting off from the seminal contribution of Baumol (1986), the use of cross-sectional growth regressions has been popularized by Barro (1991) and Barro and Sala-i-Martin (1991a, b, 1992). The hypothesis being tested is that, during the adjustment process to the steady state, the growth rate of an economy over a given period of time is inversely related to the initial per-capita income level. Hence, the question is whether economies with low initial levels of per capita income experience the fastest growth rates.

Mankiw, Romer, and Weil (1992) generalize this absolute convergence hypothesis by allowing each particular economy to approach its own steady state. The empirical implication of this notion of conditional convergence is that initial income differences between independent countries or regions will not necessarily diminish because convergence occurs to one's own steady state.

Later, these regressions have been extended to panel data models in order to control for unobserved heterogeneities and to deal with endogeneity problems (Islam, 1995, Caselli, Esquivel, and Lefort, 1996, Lee et al. (1998), Bond, Hoeffler, and Temple, 2001). Another empirical strategy within the regression approach relies on time-series techniques. As such, time-series tests of convergence are usually carried out using tests for unit roots and cointegration (Evans and Karras, 1996a, b, Carlino and Mills, 1993, 1996a, b, Bernard and Durlauf, 1995, 1996). Finally, there is an evolving literature that focuses on the consequences of spatial interaction effects on convergence (see for example Rey and Montuori, 1999, López-Bazo et al., 1999, Niebuhr, 2001).

From the survey article by Magrini (2004) one gets the impression that the literature is reaching a point of decreasing returns in terms of extending the regression approach to convergence (see Bode and Rey (2006) for a similar conclusion concerning spatial econometric extensions of the regression approach). In fact, genuine progress seems hard to achieve within the regression approach. There are at least two major factors which explain this tendency. One factor is the fundamental critique put forth by Levine and Renelt (1992) and Levine and Zervos (1993), and the second factor is the critique put forth by Friedman (1992) and Quah (1993).

Levine and others perform a sensitivity analysis of a huge number of variables that appeared in cross-country growth regressions. The overall pattern is that the estimated coefficients are not very robust against a variation in the set of conditioning variables. The point of Friedman (1992) and Quah (1993) is more methodological in nature and concentrates on the informative content of cross-sectional regressions. Their main criticism is that the regression approach tends to concentrate on the behavior of the representative economy whilst giving no information on the dynamics of the entire cross-sectional distribution of regional incomes. In other words, there is an analogy between regressions of growth rates over initial levels and Galton's fallacy of regression towards the mean. As summarized by Magrini (2004, p. 10), a 'negative relationship between growth rates and initial values does not indicate a reduction in the cross-sectional variance and, moreover, it is also possible to observe a diverging cross-sectional distribution even when such a negative relationship holds'.

It is this last criticism that has motivated Danny Quah to develop the 'distribution dynamics approach' to economic convergence. This approach examines directly how the cross-sectional distribution of per capita income develops over time. Although the distributional approach to convergence is not without problems of its own, the overall conclusion of the survey article by Magrini (2004) is that

> '[...] the distributional approach to convergence—particularly when based on nonparametric stochastic kernel estimations—appears to be generally more informative than convergence empirics within the regression approach, and therefore represents a more promising way forward' (Magrini, 2004, p. 3).

In **Part I** of my thesis I use methods from both, the regression approach and the distribution dynamics approach to analyze regional convergence in Germany. The essays presented in Chapters 2 and 3 do not aim at providing an overview of the key developments in the study of regional convergence, nor do they attempt to provide a balanced view of the literature. Rather, I discuss and extend the self-contained empirical studies of Bayer and Jüßen (2006) and Jüßen (2006a).

**Chapter 2** presents the paper 'Convergence in West German Regional Unemployment Rates' published in Bayer and Jüßen (2006). According to the above classification of convergence empirics this paper belongs to the regression approach. Specifically, we use a time-series approach to economic convergence. There is a clear economic motivation to stick to this empirical strategy: One central aspect of this paper is to account for a structural break in the data series employed and the time-series approach is a powerful tool to address this issue. Moreover, Bernard and Durlauf (1996) illustrate that this approach appears to resort a stricter notion of convergence than cross-sectional analyses.[2]

[2] In many cases, the lack of adequately extended series of data at the regional level hampers the general application of the time-series approach. The data series employed in Bayer and Juessen (2006) have the particular advantage of covering a comparatively long period of time, namely from 1960-2002.

One novelty of Bayer and Jüßen's (2006) paper is that it extends the established time-series approach to another area in economics. While most studies have focused on convergence in per capita output or related productivity measures, we borrow the techniques from the growth convergence literature to examine the evolution of regional disparities in unemployment rates within a country, a topic that has gained much attention since the seminal paper of Blanchard and Katz (1992). For Germany, our study is the first one analyzing the convergence of regional unemployment rates at the federal state level.

Differences in regional unemployment rates are often used to describe regional economic inequality. In our paper we paper ask whether changes in regional unemployment differences in West Germany are persistent over time. Understanding the persistency of regional unemployment differences helps us to asses how effective regional policy can be. While univariate tests suggest that changes in unemployment differences are persistent, more powerful panel tests lend some support to the hypothesis that regional unemployment rates converge. However, these tests reveal a moderate speed of convergence at best. Since there is a structural break following the second oil crisis, we also employ tests that allow for such a break. This provides evidence for both, convergence and quick adjustment to an equilibrium distribution of regional unemployment rates that is subject to a structural break.

Our finding of structural breaks has important implications for policies targeted at regional unemployment rates. If there is regime-wise conditional convergence and fast equilibrium adjustment, then this implies on the one hand that small government interventions loose their effect quickly as unemployment rates adjust back to their equilibrium levels. On the other hand, large interventions might move the economy from one equilibrium to the other. Hence, policy intervention needs to take the form of a substantial regime shift.

In **Chapter 3** I move to the alternative approach to convergence, namely that of distribution dynamics. As discussed above, one fundamental criticism of the regression approach is that it tends to concentrate on the behavior of a representative economy, whilst ignoring the dynamics of the entire cross-sectional distribution. Therefore, proponents of the regression approach suggest to extend cross-country growth regressions by additionally examining the development of dispersion of per capita income levels or growth rates (Barro and Sala-i-Martin, 1991). If the dispersion of the cross-section income distribution is declining over time, $\sigma$-convergence is said to hold ($\sigma$ is the notation for the standard deviation of the income distribution). Friedman (1992) and Cannon and Duck (2000) show how the concept of $\sigma$-convergence can be applied in a regression framework.

The overall conclusion of the survey articles by Durlauf, Johnson, and Temple (2004) and Magrini (2004) is, however, that existing formulations of $\sigma$-convergence are not fully satisfactory. There are at least three major reasons for this. Firstly, there is no straightforward way to implement a notion of conditional $\sigma$-convergence. Secondly, analyzing the change of cross-sectional dispersion as measured by standard deviation or coefficient of variation means focusing on only one single moment of the underlying distribution. Thirdly, a constant standard deviation is consistent with very different dynamics ranging from 'criss-crossing and leap-frogging to persistent inequality and poverty traps' (Magrini, 2004, p. 32). Further problems concerning the interpretation of tests of $\sigma$-convergence are pointed out by Bliss (1999, 2000).

Danny Quah has developed an alternative approach to analyzing convergence that overcomes the discussed limitations of the $\beta$- and $\sigma$-convergence concepts. It is widely accepted that his distribution dynamics approach represents a radical departure from the regression approach. Instead of focusing on single moments of the underlying (output or income) distribution as it is the case for traditional $\beta$- and $\sigma$-convergence approaches, Quah suggests to examine directly how the entire cross-sectional distribution changes over time. This innovative approach is able to illustrate the change in the shape of the income distribution and is additionally informative about the degree of mobility of individual countries or regions in the ranking of incomes. These mobility patterns are referred to as 'intra-distribution dynamics'.

To illustrate the multiplicity of studies which adopt Quah's techniques, Table 1.1 presents a list of recent papers which use the distribution dynamics approach to analyze growth and convergence in various countries and regions.[3] My paper 'A Distribution Dynamics Approach to Regional GDP Convergence in Reunified Germany' (Jüßen, 2006a) complements these studies by examining convergence of GDP per worker across German labor market regions during 1992 to 2002.

While there are several studies analyzing regional convergence in West Germany[4], empirical evidence regarding reunified Germany is still scarce. Kos-

[3] This list may be incomplete and does not comprise Quah's own contributions. Some notable excpetions which use Quah's techniques in another area of economic research are the studies of Overman and Puga (2002) and Lopéz-Bazo, del Barrio, and Artis (2005), which assign Quah's ideas to a labor market framework.

[4] See Seitz (1995), Schalk and Untiedt (1996), Kellermann (1997), Bohl (1998), Funke and Strulik (1999) and Niebuhr (2001). In general, these studies do find evidence for both, absolute and conditional convergence in West Germany.

Table 1.1: Studies which use Quah's distribution dynamics approach in the field of growth and convergence

| Study | Uses data for... | Field of research |
|---|---|---|
| Andrade et al. (2004) | Brazilian municipalities | Output per capita convergence |
| Bandyopadhyay (2002, 2004) | Indian states | Income per capita convergence |
| Epstein, Howlett, and Schulze (2003) | OECD countries | GDP convergence |
| Fiaschi and Lavezzi (2004) | 15 countries | Long-run output growth |
| Fotopoulos (2004) | EU-15, NUTS 2 regions | Labor productivity convergence |
| Johnson (2000) | US federal states | Income per capita convergence |
| Johnson (2005) | Countries in Penn World Tables | Convergence in output per capita, TFP, capital-output ratio, human capital per worker |
| Jüßen (2006a) | German labor markets | Output per worker convergence |
| Kang (2004) | Japanes prefectures | Income per capita convergence |
| Kremer, Onatski, and Stock (2001) | 140 countries, Penn World Tables | Output convergence |
| López-Bazo et al. (1999) | EU regions | Output per capita convergence |
| Magrini (2004) | EU NUTS and functional regions | Income convergence |
| Maza and Villaverde (2004) | EU NUTS 2 regions | Output per capita convergence |
| Mossi et al. (2003) | Brazilian states | Income per capita convergence |
| Pittau and Zelli (2004) | EU-12 regions | Household and size-adjusted income convergence |
| Pittau and Zelli (2005) | European regions | GDP per capita convergence |
| Pittau (2005) | European regions | GDP per capita convergence |
| Tortosa-Ausina et al. (2005) | Spanish provinces | Convergence in output, TFP, capital intensity |

feld, Eckey, and Dreger (2002) and Kosfeld and Lauridsen (2004) adopt spatial econometric techniques to analyze convergence in reunified Germany. Since pronounced East-West disparities are a well-documented fact in reunified Germany (Barell and te Velde, 2000), I extend these regression-based studies by using nonparametric techniques which are especially useful in uncovering empirical phenomena like polarization and clustering.

I find that there is evidence for a tendency towards convergence during the observed period, i.e. regions that were less productive in 1992 (East German regions) established a higher relative GDP in 2002. It is an advantage of the empirical approach that it allows one to make predictions about the long-run distribution of regional production. Regions in reunified Germany will not become equal to one another in terms of GDP per worker if the observed distributional dynamics remain unchanged. I predict a pronounced polarization in the long-run distribution of regional GDP which reflects a long-run heterogeneity among West and East German regions.

## 1.2 Part II: Risk Sharing in Germany and the US

In **Part II** I approach the effects of openness on regional income differences and convergence from a completely different perspective, namely that of interregional risk sharing. This part of the thesis consists of two self-contained papers: the one published in Jüßen (2006b) ('Interregional Risk Sharing and Fiscal Redistribution in Reunified Germany') and my paper 'Home Bias, Neighborhood Bias, and Incomplete Capital Market Risk Sharing among US Federal States' (Jüßen, 2006c). Because some general issues concerning risk sharing are closely related, both chapters will naturally touch on each of them. Moreover, there are some redundancies between Chapters 3 and 4 because I use similar econometric techniques in both chapters.

At the heart of interregional risk sharing stand the fundamental differences between regional Gross Domestic Product (GDP) and regional income. While GDP corresponds to a region's production and hence attributes to a region the amount of economic production generated within it, income explicitly includes net factor payments from other regions. Thus, income equals output plus net factor income flows.

The general idea of risk sharing is that, by holding claims to output produced in other regions, individuals can smooth away shocks to their own income caused by variations in their home region's production. This means that individuals can share their output risk by diversifying their asset portfolios, i.e., via cross-ownership of productive assets. Following the seminal paper of Asdrubali, Sørensen, and Yosha (1996) such insurance is referred to as 'income smoothing' or 'capital market smoothing'. As long as output across regions is imperfectly correlated, this kind of income insurance is effective for smoothing both, permanent and transitory shocks to output (see Becker and Hoffmann, 2006).[5]

As discussed by Asdrubali, Sørensen, and Yosha (1996) and von Hagen (2000), in a world with imperfect capital markets, further smoothing of incomes can be achieved by the fiscal transfer system, which renders disposable income

[5] Throughout the thesis I use the words 'risk sharing', 'insurance' and 'smoothing' interchangeably.

different from income. For instance, the government may provide risk sharing via the tax transfer system or by allocating grants and subsidies to economies which suffer from an economic downturn. This channel of risk sharing is referred to as 'federal government smoothing'.

Lastly, individuals may adjust their savings behavior in response to shocks and further smooth their consumption by borrowing and lending on the credit market. This ex-post channel is referred to as 'consumption smoothing' or 'credit market smoothing'. According to models of forward looking consumer behavior (permanent income theory), consumption smoothing can only be effective if shocks are perceived as transitory. This means that the credit market is a close substitute for income insurance provided by the capital market if shocks to output are not very persistent (see Baxter and Crucini, 1995). If some shocks are not smoothed at all after all three channels of smoothing—i.e., after capital market, federal government, and credit market smoothing—full risk sharing is not achieved.

The important empirical implication of risk sharing theory is closely related to the key implication of complete financial markets: fluctuations in idiosyncratic marginal utility growth should be independent of idiosyncratic (output) risk. Therefore, in the presence of complete risk sharing, the coefficient of a regression of relative consumption growth on relative output growth should be zero. Similar regressions have been conducted at the microeconomic level, see for example Mace (1991), Cochrane (1991), and Townsend (1994). The overall pattern found by these studies is that full risk sharing has to be rejected.

At the macroeconomic level, the issue of (aggregate) risk sharing has been popularized by Sala-i-Martin and Sachs (1992), von Hagen (1992), Atkeson and Bayoumi (1993), Obstfeld (1994a, b), Canova and Ravn (1996), Lewis (1996), and others. The prevalent motivation of these papers is to analyze the pros and cons of a monetary union and its consequences for macroeconomic stabilization (see also Eichengreen, 1990). Specifically, the early macroeconomic risk sharing literature addresses the concern that adverse output shocks to individual member states of the currency union in Europe can no longer be blunted by independent monetary policy.

One contribution of particular importance is that of Asdrubali, Sørensen, and Yosha (1996). This paper shows how to measure the amount of aggregate risk sharing that is achieved through the various channels discussed above and applies the proposed method to risk sharing among US federal states. Sørensen, and Yosha (1998) take this approach to the international economy and analyze risk sharing among EU and OECD countries. The method developed by Asdrubali, Sørensen, and Yosha (1996) has been extended by Mélitz and Zumer (1999), who take differences in demographic and other factors into account and analyze their consequences for risk sharing. Further work in this topic includes Hess and Shin (1998), Crucini (1999), Crucini and Hess (2000), Athanasoulis and Wincoop (2000, 2001), Del Negro (2002), and Kalemli-Ozcan, Sørensen, and Yosha (2003, 2004). The most recent extension in the macroeconomic literature on risk sharing is proposed by Becker and Hoffmann (2006), who focus on dynamic aspects of risk sharing and account for transitory and persistent components of macroeconomic shocks (see also Asdrubali and Kim, 2004).[6]

In Chapters 4 and 5 I contribute to the literature on macroeconomic risk sharing, again by taking an intranational perspective. Regional risk sharing is one of the themes that has received considerable attention because it is of utmost importance to understand the extent of capital market integration at the regional level as compared to the international level, especially against the background of proceeding European integration.

Both papers presented in Part II are similar in introducing new econometric techniques for applied work on risk sharing. In the first paper (Chapter 4), I transfer the distribution dynamics approach to economic convergence to a risk sharing setting. In the second paper (Chapter 5), I use spatial econometric techniques to analyze local biases in factor income flows among US federal states. While both empirical methodologies have been extensively used in the fields of economic growth and convergence, they are—to the best of my knowledge—new to the risk sharing literature. Therefore, one contribution of the second part of my thesis is a cross-fertilization between the modern literature on growth econometrics and the macroeconomic literature on risk sharing.[7]

In one of his influential papers Danny Quah suggested that his distribution dynamics approach may turn out to be useful in other areas of economic research, too, in which phenomena like clumping, stratification, and polarization potentially play a role (Quah, 1996b):

[6] The literature on aggregate risk sharing is closely related to the literature on international real business cycles. Backus, Kehoe, and Kydland (1992), Baxter and Crucini (1995), and Stockman and Tesar (1995) derive consumption correlations from two-country general equilibrium models with complete financial markets. In international macroeconomic data, consumption correlations are found to be substantially lower than predicted by these models. This finding is referred to as the 'international consumption correlation puzzle'. Hess and Shin (1998) provide evidence that this puzzle does also apply for US federal states. However, Stockman and Tesar (1995) have shown that low consumption correlations may be explained by preference shocks. Additionally, measurement error may play an important role.

[7] For a comprehensive survey of the various econometric tools that have been employed to study economic growth and convergence I refer to Durlauf, Johnson, and Temple (2004).

> ‘Examples where these [phenomena] are relevant include industry evolutions; economic geography, location dynamics, and regional business cycles; consumption risk sharing; asset market comovements; personal income distributions and intergenerational income mobility; and disaggregate price inflactions’ (Quah, 1996c, p. 117).

In **Chapter 4**, I take Quah’s general suggestion literally and bring together the distribution dynamics approach with the macroeconomic literature on risk sharing. In my paper ‘Interregional Risk Sharing and Fiscal Redistribution in Reunified Germany’ published in Jüßen (2006b), I suggest a modification of Quah’s approach to examine two related questions: First, to what extent do private institutions and the public sector provide insurance against idiosyncratic shocks to individual regions? Second, to what extent does the public sector reduce long-term differences between regions?

While the federal government channel is not found to have a stabilizing effect, private factor income flows provide almost complete insurance against short-term shocks. A co-movement of income and output is only found for high and low idiosyncratic output risk. This pattern could not be detected within a linear regression approach.

In sharp contrast, the fiscal transfer system achieves a substantial reduction of long-term disparities between regions. If past distribution dynamics continue operating unchanged in the future, a uni-modal distribution of regional incomes will not be achieved without redistribution by the public sector. This result shows that fiscal transfers in reunified Germany are mainly concerned with redistribution in favor of depressed regions rather than providing insurance against idiosyncratic shocks.

My paper provides strong evidence that the redistributive policy which is responsible for the wedge between income and disposable income has no stabilizing effects as a by-product, at least at the disaggregated regional level used in my paper. Therefore, it is hard to argue that short-term risk sharing is one justification of the federal transfer mechanism in reunified Germany. Taken as a whole, my results imply that the public sector provides insurance against that type of risk which cannot be completely insured on private markets: The risk of being a permanently poor region.

In **Chapter 5** I draw from recent advances in spatial econometric techniques to examine capital market risk sharing among US federal states. Up until today, researchers have not devoted much effort to adjusting empirical (or theoretical) risk sharing models to incorporate spatial interdependencies.

This is surprising because recent advances in spatial static and dynamic panel data econometrics offer the opportunity for exploiting both, the time-series, the cross-sectional, and the spatial information of macroeconomic data simultaneously (see for example Elhorst, 2003, Anselin, Florax, and Rey, 2004, Korniotis, 2005, Kapoor, Yang, Li, and Tse, 2006, Kelejian, and Prucha, 2006).[8]

Already the early study of Cochrane (1991) emphasizes that spatial effects may be of relevance for risk sharing and consumption smoothing. Specifically, Cochrane (1991, p. 974) concludes that consumption insurance may hold more closely among groups that are geographically close than it does in society at large, since by regular contact such groups are better able to work out informal implementation mechanisms. Similarly, Rose and Engel (2002) find that consumption insurance between country pairs declines with distance. Spatial econometric techniques lend themselves as a natural way to model such issues head-on.

One specific application of spatial econometric techniques is presented in Chapter 5. In my paper 'Home Bias, Neighborhood Bias, and Incomplete Capital Market Risk Sharing among US Federal States' (Jüßen, 2006c), I show how spatial models provide a parsimonious approach to address local biases in factor income flows and their consequences for aggregate risk sharing among US federal states. My paper extends recent research which has examined the relationship between the well-documented 'home bias' in portfolio holdings and the degree of risk sharing that is achieved among OECD countries (see Sørensen, Wu, Yosha, and Zu, 2005, and Artis and Hoffmann, 2005).

At the regional level, we would expect that biases in portfolio holdings manifest themselves in a more complex way than a pure home bias. In particular, we would expect that regional asset portfolios are characterized by a disproportionate high fraction of assets issued in geographically close areas—but not necessarily the home region.

Indeed, there is considerable evidence from micro-based studies which analyze individual investment portfolios directly that the home bias within the US manifests itself in such a complex way. The preference for investing close to one's home is related to distance, information asymmetries, and familiarity biases (see Coval and Moskowitz, 1999, Huberman, 2000, 2001). Therefore, we may think of the home bias within a country in more general terms as a 'local bias', which may consist of a pure 'home bias at home', but also of a 'neigh-

[8] As mentioned above, these techniques have been extensively used in the field of regional economic growth and convergence (see for example the various papers published in the recent special issue of *Papers in Regional Science,* edited by Bode and Rey, 2006).

borhood bias'. I interpret the 'neighborhood bias' as a bias which is related to economic distance and geographical proximity. Obviously, the neighborhood bias is at odds with the diversification of risk.

In my paper I propose a new approach which allows me to address the neighborhood bias and its consequences for risk sharing at the regional level: I extend the standard risk sharing model to a spatial model. One particular advantage of the spatial model is that it can be estimated using the same macroeconomic data that is usually used to study risk sharing among US federal states.[9] With the spatial model I examine whether the fluctuation of *factor income flows* between states and their neighbors is disproportionately high—in comparison to a balanced portfolio which assigns fair weights to each others output.

Factor income flows comprise capital income flows between states, such as dividends from cross-holdings of productive assets. Therefore, factor income flows are responsible for the amount of capital market risk sharing that is achieved. Especially at the regional level, however, factor income flows do also reflect income flows associated with the factor labor. For instance, if workers commute to their place of work in another federal state, their output is measured at their place of work while their income is attributed to their place of residence. Therefore, I extend my analysis to account for commuter flows across states in order to test whether a neighborhood bias in factor income flows is indeed a phenomenon which should be attributed to the capital market (i.e., reflects a neighborhood bias in portfolio holdings), or if labor income flows also play a role.

Similar to previous studies, I find that insurance against own idiosyncratic shocks has increased substantially over time. This means that state-level income has become more and more buffered against region-specific shocks to GSP. At the same time, however, factor income flows have become substantially biased towards neighboring states in recent years. As a consequence, state-level income co-moves not only with own idiosyncratic output fluctuations, but also with output growth of neighboring states. Therefore, my study suggests that the overall amount of income insurance that is achieved in recent years is more limited than reported in previous studies which did not take the neighborhood bias into account.

[9] See for example Asdrubali, Sørensen, and Yosha (1996), Sørensen and Yosha (1998), Mélitz and Zumer (1999), Athanasoulis and van Wincoop (2001), Asdrubali and Kim (2004), Asdrubali and Kim (2005), Kalemli-Ozcan, Sørensen, and Yosha (2004), Becker and Hoffmann (2006).

When I incorporate commuter flows into the analysis I find that a fictitious federal state, which is completely isolated from other states in terms of commuting, is not subject to a neighborhood bias in factor income flows—at least the statistical significance of the neighborhood bias vanishes for this state. Thus, the apparent neighborhood bias in factor income flows does not primarily reflect a preference for geographically proximate investments, but rather the effect of commuting linkages among states. I believe that this result is of utmost importance since it also suggests that risk sharing itself is not an issue of capital markets solely.

With unemployment, growth convergence, and risk sharing the papers presented in this thesis range across a variety of economic applications. They are united in the common goal of establishing a cross-fertilization between the modern literature on growth econometrics and other areas of economic research. I will come back to this issue in **Chapter 6** in which I present some concluding remarks. Chapter 6 is followed by two **Appendices** that contain additional material omitted in the text.

# Part I

# Regional Convergence in Germany

# Chapter 2

# Convergence in West German Regional Unemployment Rates

## 2.1 Introduction

The extensive literature on economic convergence between countries and regions focuses mostly on per capita income or other related income and productivity measures. This focus may be fruitfully extended to other areas in economics, as Quah (1996b, p. 1354) has pointed out:

> 'Certainly, understanding economic growth is important. But growth is only one of many different areas in economics where analyzing convergence sheds useful insight.'

Following Quah's general suggestion, this paper borrows techniques from the literature on growth convergence. We use these techniques to examine the evolution of regional disparities in unemployment rates within a country, a topic that has gained much attention since the seminal paper of Blanchard and Katz (1992).

Unemployment disparities are often perceived as persistent. They are at the heart of the 'regional problem' and in the focus of regional economic policy (Armstrong and Taylor, 2000). Thus, their persistence has attracted much attention.[1]

Persistency itself may reflect stable equilibrium differentials of regional unemployment rates or may be attributed to the fact that shocks to regional unemployment rates have long-lasting effects, see Martin (1997). Discriminating between these two cases is important because policy interventions are more

[1] See for example Decressin and Fatas (1995) or Obstfeld and Peri (1998).

likely to be effective in the latter case. On the contrary, if the differences reflect an equilibrium that has been stable over time, (short-term) policy interventions are less likely to change this stable equilibrium.

It is thus interesting in particular in the German context to study whether regional unemployment rates converge to the national average over time. As the federal government in Germany aims to reduce the gap between unemployment rates in East and West Germany by granting subsidies and by spending on public infrastructure, it is of importance to understand how fast convergence happens.

In order to understand how quickly unemployment rates converge, we employ aggregated annual data from the 'Mikrozensus' database on unemployment rates for the West German federal states during the period 1960-2002. We analyze convergence using the stochastic approach that was proposed by Bernard and Durlauf (1995, 1996) and Carlino and Mills (1993, 1996a, b). This means that our study characterizes the evolution of the gap between the unemployment rate in a specific federal state and the unemployment rate in Germany as a whole.

For the US, Blanchard and Katz (1992) have analyzed the dynamics of regional employment and unemployment. While they do not explicitly find evidence for stationarity of regional unemployment rates, they attribute this to a power problem of the tests they apply. Indeed, Decressin and Fatas (1995) and Obstfeld and Peri (1998) provide some evidence that regional unemployment disparities are a more persistent phenomenon in Europe than in the US. However, these results have recently been questioned by Rowthorn and Glyn (2003) who do find substantial persistence also in US regional unemployment rates. For the UK, by contrast, Martin (1997) finds that regional unemployment shocks are only short-lived. Yet, he also finds that regional unemployment rates differ in the long run, which reflects a stable equilibrium distribution around the national average.

For Germany, our study is the first one analyzing convergence of unemployment rates at the federal state level. There are a number of studies which examine the related issue of hysteresis for West German unemployment rates: Balz (1999), Belke (1996), Belke and Göcke (1996), Camarero and Tamarit (2004), Hansen (1991), and Reutter (2000). However, these studies analyze the absolute level of aggregate or regional unemployment rates and not relative unemployment rates as we do. As a consequence, these papers cannot shed much light on convergence.

The main results of our study are the following. While univariate techniques which do not account for structural breaks do not provide evidence for stochastic convergence in relative unemployment rates, more powerful panel-based methods allow us to infer that there is convergence. At the same time, the panel-based methods also suggest that the speed of convergence is slow. The estimated half-life of a shock to regional unemployment is at least 5.6 years.

However, this degree of persistence may be over-estimated. There is a structural break in the data following the second oil crisis as a graphical analysis reveals. In order to find out how strongly this break drives our previous results of non- or slow convergence, we subsequently apply an empirical framework that is robust to the existence of a structural break. This structural break is specified as an endogenously determined single level shift in the mean of the unemployment rate of each federal state relative to Germany as a whole. Under this specification, we can reject the null hypothesis that shocks to unemployment differences persist. Rather, the tests give evidence for conditional convergence in most regions. This conditional convergence means that regional unemployment rates converge up to a constant difference to the national average, but this difference is subject to a one-time permanent shift, which occurred following the second oil crisis. Moreover, allowing for a structural break, the estimated speed of convergence increases substantially, so that the estimated half-life goes down from 5.6 to less than 2 years on average. Consequently, persistency in regional unemployment disparities reflects an equilibrium to which the German economy adjusts quickly.

The remainder of this paper is organized as follows: Section 2 introduces the theoretical concepts. After describing the data in Section 3, we begin with a graphical analysis, which serves as a guideline for the rest of the paper. Section 4 provides the analysis of convergence on the basis of univariate and panel unit-root tests which do not account for structural breaks. This analysis is extended to the possibility of a structural break in Section 5. Finally, Section 6 discusses our results and Section 7 concludes.

## 2.2 Theoretical concepts

When labor markets adjust towards equilibrium in the long run, there will be convergence of regional unemployment rates, because unemployed workers take jobs in other areas or because capital flows into low-wage regions to take advantage of lower labor costs (for details, see Blanchard and Katz, 1992).

However, if the speed of adjustment is slow, unemployment disparities may arise during adjustment as a result of negative demand shocks affecting some regions more than others (Armstrong and Taylor, 2000).

We can test this theory of long-term convergence empirically by using Bernard and Durlauf's (1995, 1996) time-series approach. This approach focuses on the permanence of shocks to *relative* variables and uses a stochastic definition of convergence (see also Carlino and Mills, 1993, 1996, a, b).

The idea of Bernard and Durlauf's test for stochastic convergence can be explained as follows. Let $ur_{it}$ and $ur_{jt}$ be the unemployment rates of regions $i$ and $j$ at time $t$, respectively. Suppose that region $i$ has a larger unemployment rate than region $j$ initially, $ur_{i0} > ur_{j0}$. The gap in unemployment between the two regions is $ur_{it} - ur_{jt}$. Define $I_t$ as the information set available at period $t$. Then, Definition 2 in Bernard and Durlauf (1996, p. 165) understands convergence as the equality of long-term forecasts at any fixed time. This means

$$\forall t : \lim_{s\to\infty} E(ur_{i,t+s} - ur_{j,t+s}|I_t) = 0. \tag{2.1}$$

Stochastic convergence implies that regional unemployment differences will always be transitory in the sense that the long-term forecast of the difference between any pair of regions tends to zero as the forecast horizon grows.

The important testable implication of this stochastic approach to long-term convergence is that convergence is present only if shocks to the unemployment differential are temporary. Hence, the disparities between regions should follow a stationary process, which means that $ur_i$ and $ur_j$ are cointegrated. Without stationarity, shocks to the relative variable lead to permanent differences.

As such, time-series tests of convergence have typically been implemented by using unit-root tests. For example, Carlino and Mills (1993) and Evans and Karras (1996a) apply Dickey-Fuller type tests for the presence of a unit root in the relative variable. If the series has a unit root, shocks are permanent and there will be no convergence. Besides precluding stochastic trends (i.e. unit-roots), long-term convergence also precludes any deterministic trends in cross-regional differences. In fact, also the mean of the series of unemployment differences should be zero under the assumption of absolute convergence.

However, the hypothesis of stationarity *and* zero means might be too strict. As an example, we can consider regional amenities that lead to wage differentials which compensate workers for differences in the quality of life or for different regional price levels. If we assume additionally that there is a national unemployment insurance that pays a fixed unemployment benefit which is equal among regions, then there will be persistent differences in unemployment rates. Because wages are lower in regions rich of amenities, the equal unemployment benefit leads to higher rates of voluntary unemployment in the amenity-rich regions. Or to put it differently, the voluntarily unemployed would move to the amenity-rich regions in this simplistic setting. This results in stable differences between regional unemployment rates, whereas these differences just reflect disparities in economic fundamentals, such as differences in natural endowments.

In such a setting, regional economic policy that wants to reduce inequality would need to aim at shifting the equilibrium. However, it is unlikely that short-term policy interventions are actually effective for this purpose, if the equilibrium has been stable over the past.[2]

To capture this notion of stable long-term equilibrium differences, we define *conditional* convergence as

$$\forall t : \lim_{s\to\infty} E(ur_{i,t+s} - ur_{j,t+s}|I_t) = constant. \tag{2.2}$$

This means that $ur_i$ and $ur_j$ converge towards a (time-invariant) equilibrium differential. An empirical test for stochastic conditional convergence is again related to the time-series properties of relative unemployment rates. Conditional convergence implies that the series is (weakly) level-stationary but it is not required that the series has a zero mean.[3]

## 2.3 Data and graphical analysis

### 2.3.1 Data

We use data that is aggregated from the German 'Mikrozensus' database by the Federal Statistical Office. The Mikrozensus is an annual collection of household data for a representative sample of German households. The aggregated data is available to the scientific user from 1957 onwards, while the microdata is available only since 1989. For this reason, we use aggregated data at the federal state level, which is available since 1957.

[2] See Marston (1985) for a more elaborated theoretical underpinning of the equilibrium and dis-equilibrium perspective of regional unemployment disparities.

[3] We can consider the series generated by the autoregressive model $u_t = \phi + \rho u_{t-1} + \varepsilon_t$ as an example. This series is stationary if $|\rho| < 1$ and the intercept $\phi$ controls the mean of $u_t$ through the relationship $E(u_t) = \mu = \phi/(1-\rho)$. If $u$ is relative unemployment, we find conditional convergence if $\rho < 1$ and unconditional convergence if additionally $\phi = 0$.

Since there was virtually no unemployment in Germany during the late 1950s, we restrict the data to the period 1960-2002. Moreover, West Berlin is excluded from the analysis because of its special status before German reunification.

The data contains information on the number of employed and on the number of unemployed persons for each federal state. In the Mikrozensus data, the term 'unemployed' refers to all people without employment contract who search for a job irrespective of being registered as unemployed or not at the German Federal Employment Agency. Therefore, the definition of unemployment in our data differs somewhat from the statistics of the German Federal Employment Agency, but is more similar to the definition of the unemployment rate used in other countries, in particular the US.[4]

Another central advantage of our data is that it spans a long period of time. The long period of time is important for our analysis for two reasons. Firstly, we want to find out whether relative unemployment rates exhibit some form of path dependency or converge alternatively. Obviously, observing the data over a long time span is crucial for such kind of analysis. Secondly, and even more importantly, the long time span allows us to assess whether regional unemployment disparities are subject to structural breaks over time. As it will turn out, allowing for structural breaks is important both, for our test results and even more so for the interpretation of the latter.

The unemployment rate (in percentage points) is defined as the number of unemployed divided by the labor force ('Erwerbspersonen') multiplied by 100. Labor force data was also derived from the Mikrozensus. According to the Mikrozensus definition, the labor force is the sum of the employed and the unemployed ('Erwerbstaetige' and 'Erwerbslose').

We denote the unemployment rate for federal state $i$ by $ur_i$ and the unemployment rate for Germany as a whole (without West-Berlin) by $ur_{Ger}$. Time indices are suppressed for notational convenience. For the period after German reunification, 1991-2002, the unemployment rate for Germany, $ur_{Ger}$, is calculated on the basis of data from West German federal states only.

As explained in the previous section, stochastic convergence requires that relative unemployment rates follow a stationary process. We compute the relative unemployment rate $u_i$ for federal state $i$ as

$$u_i = ur_i - ur_{Ger}. \tag{2.3}$$

[4]Annual data on *registered* unemployment at the federal state level is available only since 1974 (depending on the federal state).

The unemployment rate for Western Germany, $ur_{Ger}$, is selected as a reference. This reflects that unemployment rates for the different federal states do not evolve differently from the national average if they converge.[5]

The typical testing strategy for convergence applies some linear model for $u_{it}$ and a test for the presence of a unit root. Since unemployment rates are relative numbers and bounded between 0 and 100 percent, also relative unemployment rates are bounded between -100 and +100 percent. Hence, one may argue that taking literally the linear model for the differences implies that non-stationarity cannot take the form of a unit-root property of $u_i$. If $u_i$ is non-stationary, this must stem from a more complicated non-linear dynamics that is path-dependent (see Amable et al., 1994 and 2005). For example, non-stationarity could originate from a threshold cointegrated process that is mean reverting outside a certain range and has a unit root inside this range. Whether one views such a process as stationary or non-stationary depends on the relevance of the reflecting boundaries. If the boundaries are close and hit often, describing the process as stationary is a good approximation. If by contrast the boundaries are hit seldom within the sample, we may best describe the sample as having a unit root, since the outside range looses relevance. Applying a unit-root test to such process reveals the importance of non-stationarity as a property to describe the sample. In other words, we understand the unit-root property as a sample property and the relevant question becomes how persistent is the process (see Blanchard and Summers, 1986).

Keeping this in mind, we apply a linear framework and approximate a test for non-stationarity by means of a test for a unit root. We may attempt to assess the appropriateness of the linear framework beforehand by inspecting how close unemployment differences get to their boundary values. In fact, we find relative unemployment rates never to be close to the bounds -100 and +100 percent.

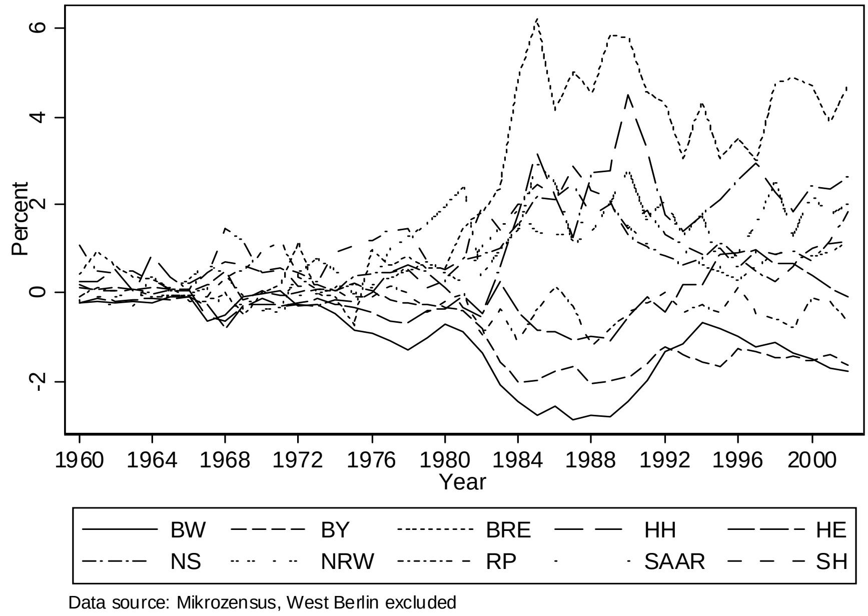
### 2.3.2 Graphical analysis

To get a first impression of the time-series characteristics of $u_i$, we display the series graphically. Figure 2.1 plots relative unemployment rates during the period 1960-2002.

It can be seen that the dispersion of unemployment rates has sharply increased in times of recessions (1966/67 and at the beginning of the 1980s)

[5] Using differences in logs or ratios of unemployment rates has the disadvantage that minor differences in unemployment rates and rounding errors get inflated by the low aggregate unemployment rates during the 1960s.

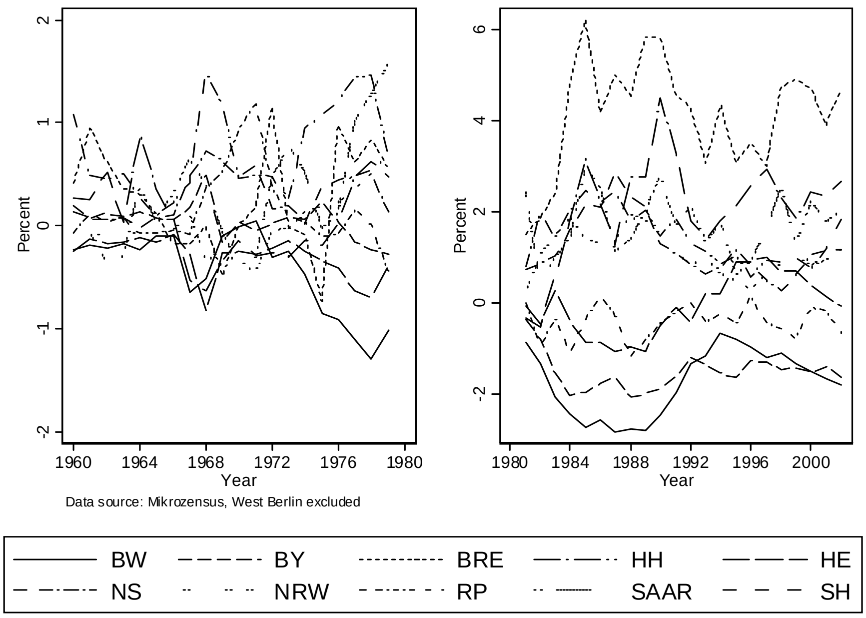
Figure 2.1: Relative unemployment rates in West Germany, 1960-2002




parallel to the increase in the aggregate unemployment rate. In the beginning of the 1960s unemployment was not a problem in Germany, in fact there was rather a shortage of labor, similarly there is not much of a difference in unemployment rates across states. After 1980 the situation is dramatically different, the dispersion of unemployment rates sharply increases with the general rise in unemployment rates. Thereafter, economic differences between the northern and southern part of Germany become apparent. Since the beginning of the 1980s, the North-German city-states Bremen and Hamburg have the highest relative unemployment rates, while Bayern and Baden-Wuerttemberg have unemployment rates around 2 percentage points below the national average.

At first glance, this makes most of the series look non-stationary. However, splitting the sample in the period before and after 1980 shows that the lack of stationarity might just be due to a single structural break that occurred in the early 1980s after the second oil crisis. In order to illustrate this, Figure 2.2 displays the data for both sub-periods; one ranging from 1960-1979 and the second from 1980-2002 (Figure 2.2). The series look more stationary now. Additionally, the two graphs illustrate that the dispersion of relative unemployment rates is significantly larger during the second sub-period than during the first one. It seems as if the levels of the series have changed due to a structural break. Finally, note that there is no apparent deterministic time trend in the data.

Figure 2.2: Relative unemployment rates in West Germany, sub-periods 1960-1979 and 1980-2002

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## 2.4 Unit-root tests without structural breaks

Having displayed the series graphically, we turn to a formal characterization of the stochastic behavior. The hypothesis being tested is that relative unemployment rates follow a unit-root process. To set the scene, we first employ a univariate unit-root test without structural breaks. As a next step, we turn to more powerful panel-based unit-root tests. Later on, we extend the analysis to allow for structural breaks.

### 2.4.1 Univariate unit-root tests

As explained in Section 2, tests of convergence can be conducted as Dickey-Fuller (1979) type tests (ADF tests) based on the difference between the unemployment rate in federal state $i$ and the unemployment rate for Western Germany:

$$\Delta u_{i,t} = \mu + (\rho - 1)u_{i,t-1} + \sum_{j=1}^{k} \varsigma_j \Delta u_{i,t-j} + \varepsilon_{i,t}, \qquad (2.4)$$

$$u_{i,t} = ur_{i,t} - ur_{Ger,t.}$$

If the series contains a unit root ($\rho = 1$), the proposition for both, absolute and conditional convergence is violated. The alternative hypothesis is that

Table 2.1: ADF test for relative unemployment rates (without trend)

**Augmented Dickey-Fuller (1979) test**

| Federal State | lags ($k$) | $\hat{\mu}$ | $\hat{\rho}-1$ | $p$-value | Federal State | lags ($k$) | $\hat{\mu}$ | $\hat{\rho}-1$ | $p$-value |
|---|---|---|---|---|---|---|---|---|---|
| BW | 1 | -.117 | -.083 | 0.402 | NRW | 5 | .099 | -.122 | 0.440 |
| | | (.066) | (.047) | | | | (.061) | (.073) | |
| BY | 5 | -.087 | -.066 | 0.658 | RP | 0 | -.071 | -.402 | 0.027** |
| | | (.061) | (.054) | | | | (.062) | (.130) | |
| BRE | 0 | .283 | -.082 | 0.650 | SAAR | 3 | .321 | -.189 | 0.547 |
| | | (.201) | (.065) | | | | (.169) | (.128) | |
| HH | 3 | .176 | -.081 | 0.791 | SH | 0 | .278 | -.241 | 0.187 |
| | | (.144) | (.091) | | | | (.133) | (.107) | |
| HE | 2 | -.044 | -.219 | 0.233 | $ur_{Ger}$ | 2 | .302 | -.038 | 0.729 |
| | | (.052) | (.103) | | | | (.191) | (.036) | |
| NS | 0 | .105 | -.108 | 0.509 | | | | | |
| | | (.072) | (.070) | | | | | | |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively.
Standard errors in parentheses.

$\rho < 1$, which implies that the series is stationary. Moreover, absolute (or unconditional) convergence implies that the constant term, $\mu$, is insignificant.[6]

The ADF-tests of convergence in relative unemployment rates are reported Table 2.1, optimal lag lengths, $k$, have been determined by sequential $t-$tests as suggested by Ng and Perron (1995). It can be seen that there are considerable differences in the time-series properties of relative unemployment rates among the federal states, but the most important result is that for nearly all federal states we cannot reject the null hypothesis of a unit root. The unit root is rejected only for Rheinland-Pfalz.

This means that the ADF tests provide no evidence of stochastic convergence during the period under study. Other studies of convergence often include

[6] We do not include a deterministic time trend in the regressions since a trend is neither compatible with long-term convergence nor apparent in our data.

a deterministic time trend in the ADF regressions. In our setting, the derived results do not depend on the absence or presence of a trend. If we allow for a time trend, results do not change. The series for Rheinland-Pfalz remains (trend) stationary and all other series remain non-stationary.[7]

### 2.4.2 Panel unit-root tests

It is well known that unit-root tests such as the ADF test have low power against stationary alternatives in small samples. Panel-based unit-root tests have proven to be more powerful, since they exploit the cross-sectional dimension of the data.

The basic regression for these panel unit-root tests is[8]

$$u_{it} = \rho_i u_{i,t-1} + z_{i,t}'\gamma + \varepsilon_{i,t} \qquad i = 1, ..., N; \; t = 1, ..., T$$

where $z_{it}$ is the deterministic component and $\varepsilon_{it}$ is a stationary error term. The set of exogenous regressors $z_{it}$ could be empty, or include a common constant, fixed effects, or fixed effects and a time trend.[9]

The Levin, Lin, and Chu (2002) test (henceforth LLC) assumes that each individual unit in the panel shares the same autoregressive coefficient: $\rho_i = \rho$ for all $i$. Hence, the power of the single ADF tests is increased not only by pooling the data but also by exploiting a cross-equation parameter restriction on the autoregressive parameters.[10] The null hypothesis of the LLC test states that the relative unemployment series of *each* state contains a unit root, which is tested against the alternative that *all* series are stationary.

The panel regressions of the LLC test include constant terms that reflect fixed effects to control for heterogeneity among cross-sectional units. In our setting, these fixed effects capture stable differences to the national average to which regional unemployment rates converge.

Since the LLC test assumes a homogeneous autoregressive coefficient, it has

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[7] We also tried the Dickey-Fuller GLS test proposed by Elliot, Rothenberg, and Stock (1996). The qualitative results are the same as obtained with conventional ADF tests. Choosing the lag length according to information criteria does neither change the results. Also Phillips and Perron (1988) tests and Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) tests yield qualitatively similar results. Detailed results are presented in Appendix A.

[8] See Baltagi (2001) for an overview of econometric methods for non-stationary panel data.

[9] In the more general case, when the error disturbances $\varepsilon_{i,t}$ are serially correlated, the serial correlation can be corrected by including lagged terms similar to the ADF procedure.

[10] The LLC test statistic converges more rapidly with respect to the time dimension $T$ than with respect to the cross-section dimension $N$. Hence, the LLC test is well-suited for our dataset with $N = 10$ and $T = 43$.

Table 2.2: Levin, Lin, and Chu and Breitung and Meyer tests for a unit root in relative unemployment rates

| **Levin, Lin, and Chu (2002) test** | | | | | **Breitung and Meyer (1994) test** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $k$ | Obs. | $\hat{\rho}-1$ | $t^{*1}$ | $P>t^*$ | $k$ | Obs. | $\hat{\rho}-1$ est.[2] | $\hat{\rho}-1$ adj.[2] | $t^{*1}$ | $P>t^*$ |
| 0 | 420 | -0.116 | -1.850 | 0.032** | 0 | 420 | -0.048 | -0.096 | -2.510 | 0.006*** |
| 1 | 410 | -0.112 | -1.643 | 0.050** | 1 | 410 | -0.040 | -0.079 | -1.980 | 0.024** |
| 2 | 400 | -0.117 | -1.307 | 0.096* | 2 | 400 | -0.040 | -0.081 | -1.938 | 0.026** |
| 3 | 390 | -0.096 | -0.013 | 0.495 | 3 | 390 | -0.013 | -0.026 | -0.617 | 0.269 |
| 4 | 380 | -0.101 | -0.026 | 0.490 | 4 | 380 | -0.017 | -0.034 | -0.772 | 0.220 |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively.
[1] $t^*$ is distributed standard normal under the null.
[2] The estimate of $\rho$ is unbiased under the null but biased under the alternative hypothesis, since $\text{plim}(\hat{\rho}-\rho)=\frac{1-\rho}{2}$. The column 'est.' displays unadjusted estimates, which are valid under the null hypothesis. The column 'adj.' displays the bias-adjusted estimates, which are valid under the alternative hypothesis. The $t^*-$statistic is computed on the basis of the unadjusted estimates, see Breitung and Meyer (1994).

a straightforward economic interpretation, which is its major advantage. We can interpret the autoregressive coefficient as a measure of the average speed of convergence in the sample. The number of years a shock needs to decay by 50% can be computed as $\frac{\ln 0.5}{\ln \rho}$. Knowing the implied half-life is important, because it allows us to compare the results of tests with and without a structural break with respect to the speed of convergence they imply. This interpretational advantage makes the LLC test our preferred testing procedure, but we consider alternative testing procedures to check for robustness.

The left-most columns of Table 2.2 summarize the results of the LLC test. The inclusion of a time trend does not change the results qualitatively. We can reject the null hypothesis of a unit root safely, if no or only one lag is included to allow for serial correlation in the error terms. If a second lag is included, we can still reject the null at the 10 percent level. Moreover, the parameter

Table 2.3: Pooled AR(1) estimation with fixed effects

| **Fixed-effects regression** | | |
|---|---|---|
| Dependent variable: $(ur_i - ur_{Ger})_t$ | | |
| constant | 0.073 | $(2.74)^{***}$ |
| $(ur_i - ur_{Ger})_{t-1}$ | 0.880 | $(36.75)^{***}$ |
| F(9, 409) = $2.38^{**}$ (indiv. effect is zero) | | |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively.
The number of observations is 420 (42 years and 10 cross-sectional units).
$t$-statistics in parentheses.
$R^2$ within is 0.79.

estimate for the autoregressive coefficient does not change substantially across the different specifications. If three or more lags are included, we cannot reject the null hypothesis anymore. Since the univariate ADF tests of the previous section suggest an average optimal lag length of roughly 2, we suppose that the model specification with two lags is most preferable. To corroborate this hypothesis, we consider LLC tests with heterogeneous lag lengths further below and select the number of lags also according to information criteria.

The parameter estimate $(\hat{\rho} - 1) = -0.117$ implies an autoregressive parameter of 0.883. This in turn means that the half-life of a shock to relative unemployment rates is 5.57 years. This seems a moderate degree of persistence.

A testing procedure similar to the LLC test is the one proposed by Breitung and Meyer (1994). This test also assumes a homogeneous autoregressive coefficient.[11] For the Breitung and Meyer (1994) test, a similar pattern emerges as for the LLC test, see the right-hand side of Table 2.2. If we use less than three lags, we can reject the null hypothesis of non-stationarity. Indeed, the bias-adjusted estimate for $\rho$ is close to the one implied by the LLC test. However, the asymptotic properties of the Breitung and Meyer (1994) test are primarily based on the size of the cross-sectional dimension. Therefore, the test results

[11] The Breitung and Meyer (1994) test has been extended to allow for a deterministic time trend by Breitung (2000).

have to be interpreted with care and the LLC test seems to be preferable.

Having shown that the time series for relative unemployment rates are jointly stationary, we estimate a simple AR(1) fixed-effects model. This allows us to formally test for unconditional convergence by testing the joint significance of the fixed-effects. The fixed-effects estimation is reported in Table 2.3. The $F-$test that all unit effects are zero is reported in the last row of the table. Since we have to reject the hypothesis that all fixed effects are insignificant, we find no evidence for unconditional convergence of regional unemployment rates.

Both, the LLC test and the Breitung and Meyer test impose the constraint that $\rho$ is homogeneous across cross-sectional units. While this constraint enables us to interpret the test statistics in economic terms, it may be too restrictive from a statistical point of view. Im, Peasaran, and Shin (2003) (henceforth IPS) propose an alternative testing procedure, which allows for heterogeneous $\rho_i$. This means that the speed of convergence may differ among regions. While the null hypothesis of the IPS test is the same as for the LLC test, the alternative hypothesis is more flexible. It states that at least one of the series is stationary but not necessarily all. The results of the IPS tests are reported in the left-most columns of Table 2.4. By and large, we find a similar pattern as with the LLC test. Again, the inclusion of a time trend does not alter our findings.

Similar to the IPS test, also the unit-root test by Sarno and Taylor (1998) allows for heterogeneous $\rho_i$. Additionally, it exploits contemporaneous correlations among the disturbances of the ADF regressions and uses a SUR-estimator for the test. Accordingly, if there is cross-sectional dependence, this estimator gains precision compared to the IPS test. On the basis of the Sarno and Taylor (1998) test, we can reject the null-hypothesis of a unit-root at all lag length considered, see the right-hand side columns of Table 2.4.

In order to find out whether our results of the panel-based tests are exceedingly sensitive to the choice of a model specification with a homogeneous lag length smaller than 3, we determine the optimal lag lengths for each state separately using three alternative criteria. The first criterion is Ng and Perron's (1995) sequential $t$-testing method, the second selection method is the Akaike information criterion (AIC) and the third one is the Schwartz criterion (BIC). For brevity, we consider the heterogeneous lag-length specifications only for an LLC test and an IPS test. Results are reported in Table 2.5. Based on the AIC, we can no longer reject the hypothesis of a unit root. Both, the BIC and sequential $t-$testing allow us to still reject the unit-root hypothesis, though only at a marginal level of significance for the IPS test.

Table 2.4: Im, Peasaran, and Shin and Sarno and Taylor tests for a unit root in relative unemployment rates

| **Im, Pesaran, and Shin (2003) test** | | | | **Sarno and Taylor (1998) test** | | | |
|---|---|---|---|---|---|---|---|
| Lags | Obs. | $W(\bar{t})^1$ | $P > \bar{t}$ | Lags | Obs. | $MADF$ | approximate critical value 5% |
| 0 | 420 | -1.958 | 0.025** | 0 | 420 | 47.268** | 22.744 |
| 1 | 410 | -1.506 | 0.066* | 1 | 410 | 45.864** | 22.974 |
| 2 | 400 | -1.615 | 0.053* | 2 | 400 | 44.383** | 23.218 |
| 3 | 390 | -0.003 | 0.499 | 3 | 390 | 31.705** | 23.476 |
| 4 | 380 | -0.099 | 0.461 | 4 | 380 | 36.337** | 23.751 |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively.
[1] $W(\bar{t})$ is distributed standard normal under the null.

For completeness, we also considered Fisher-type tests as suggested by Maddala and Wu (1999) and Choi (2001). Surprisingly, these tests cannot reject the null hypothesis of a unit-root.[12] The result is puzzling insofar as the Fisher-type tests have been designed to alleviate a potential power problem that has been attributed to LLC tests.[13]

Overall and in summary, the panel-based tests show some support for conditional convergence of relative unemployment rates during the period 1960-2002. However, the estimated speed of convergence is slow at best and differences in unemployment rates do not disappear completely over time. If the panel-based tests suggest convergence, then they also suggest that there is a stable distribution of relative regional unemployment rates, i.e. there is conditional convergence only.

Though, the graphical analysis of the time series for relative unemployment rates suggested that there might be a structural break in the means of the series.

[12] Detailed results are presented in Appendix A.

[13] However, the gain in power by the Maddala and Wu (1999) test is most pronounced when a time trend is included into the regressions. In fact, Table 1 in Maddala and Wu (1999) suggests that the Maddala and Wu (1999) test may be less powerful than the LLC test for the size of our sample if there is no trend in the data.

Table 2.5: Levin, Lin, and Chu and Im, Peasaran, and Shin tests for a unit root in relative unemployment rates with heterogeneous lag lengths

| **Levin, Lin, and Chu (2002)** | | | | | **Im, Pesaran, and Shin (2003)** | | | |
|---|---|---|---|---|---|---|---|---|
| Criterion | Obs. | $\rho - 1$ | $t^{*1}$ | $P > t^*$ | Criterion | Obs. | $W(\bar{t})^2$ | $P > \bar{t}$ |
| Seq. $t$-tests | 401 | -0.117 | -1.478 | 0.070* | Seq. $t$-tests | 401 | -1.249 | 0.106 |
| AIC | 395 | -0.110 | -1.226 | 0.110 | AIC | 395 | -1.173 | 0.120 |
| BIC | 411 | -0.109 | -1.541 | 0.062* | BIC | 411 | -1.339 | 0.090* |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively.
[1] $t^*$ is distributed standard normal under the null.
[2] $W(\bar{t})$ is distributed standard normal under the null.

Hence, our conclusion of sluggish convergence may be premature. If there is a structural break indeed, the estimated degree of persistence will be biased upwards. The interesting question is whether accounting for the structural break allows us to reject the unit-root hypothesis more clearly and changes the estimated speed of convergence substantially.

## 2.5 Unit-root tests with structural breaks

As displayed in Figure 2.1, the relative unemployment rates for the federal states seem to change permanently about 1980. After 1980, the northern regions, especially the city-states Bremen and Hamburg, exhibit a higher level of unemployment, while the southern states, e.g. Bayern and Baden-Wuerttemberg, experience below average unemployment.

This observation calls for the inclusion of a structural break in the analysis. It also explains why relative unemployment rates are only found to converge conditionally. Absolute convergence implies a zero mean of the relative unemployment series at all times, so that there cannot be structural change. By contrast, conditional convergence implies an equilibrium relationship of regional unemployment rates and the stationarity of their distribution. If the equilibrium relation is non-unique, a major shock may shift the economy from one equilibrium to the other and relative unemployment rates are only regime-wise stationary. With this regime-wise stationarity, conditional convergence with a structural break implies on the one hand that there is an equilibrium relationship between the unemployment rates of the various states in the absence of major shocks, i.e. regional shocks have no persistent effect. On the other hand, a permanent change of the equilibrium relationship occurs when the regime shifts because of a one-time major shock. To put it simple, if we find evidence for a structural break and convergence, then only very few regional shocks have persistent effects, most of them do not.

Although a theoretical explanation of an apparent level shift is interesting and important (Hansen, 2001), we only try to find the structural break and test for convergence in this paper. A theoretical explanation could for example be based on induced technological change, hysteresis effects, differences in regional specialization, or differences in union density and bargaining power, see Martin (1997) for further examples. We will come back to this issue in Section 6.

### 2.5.1 Test procedure

Since we do not specify a structural model for the regime shift, we go back to the univariate time-series approach but extend the model to allow for a one-time level shift. The timing of the level shift, i.e. the structural break, is determined endogenously and data-dependent. This approach follows the testing procedure introduced by Perron (1990), who has shown that conventional ADF tests perform poorly when there is a structural break in the means of the series. Unless the break is accounted for, a conventional unit-root test will falsely suggest non-stationarity of data that is generated by a stationary process which is subject to a structural break. This suggests that the univariate tests presented in Section 4 may have been unable to reject the unit-root hypothesis because of a permanent change in the level of the series about 1980. Similarly, this structural break may also drive the moderate speed of convergence we find on the basis of the panel-based tests.

The original approach proposed by Perron (1990) requires the break date to be known to test for a unit root in the presence of a structural break. Since we do not want to specify a certain break date a priori, we employ the Perron and Vogelsang (1992) test instead which determines the breaking date data-dependent.

Perron and Vogelsang (1992) propose two alternative models to describe the transition of the time series from the old to the new level. The first alternative, labelled 'additive outlier model' (AO), assumes the transition to happen instantaneously after the break has occurred. The second alternative, the 'innovational outlier model' (IO), assumes the break to affect the time series just as temporary shocks to the series. Hence, the adjustment to a new equilibrium occurs slowly over time in this model. The graphical analysis in Section 3 suggested that adjustment after a level shift needs some years to take effect and does not occur instantaneously (see Figure 2.1). Consequently, the IO model is more appropriate for our data.[14]

The IO model of the Perron and Vogelsang (1992) test can be described as follows. Let $T_b$ denote the date of the break with $1 < T_b < T$, where $T$ is the sample size. The null hypothesis is specified as

$$u_{i,t} = u_{i,t-1} + \psi(L)(e_t + \theta D(TB)_t), \qquad t = 2, ..., T \tag{2.5}$$

where $\psi(L)$ defines the moving average representation of the ARMA noise function. The dummy variable $D(TB)_t$ is set to 1 if $t = T_b + 1$ and 0 otherwise. The dummy $D(TB)_t$ is a one-off impulse dummy which changes the level of the series after the break by $\theta$ under the null hypothesis of a unit root. The long-term impact of the level change is given by $\psi(1)\theta$.

Under the alternative hypothesis of stationarity, the model is represented by

$$u_{i,t} = a + \phi(L)(e_t + \delta DU_t), \qquad t = 2, ..., T \tag{2.6}$$

where $\phi(L)$ defines the moving average representation of the ARMA noise function under the stationary alternative. The dummy variable $DU_t$ is equal to 1 if $t > T_b$ and 0 otherwise. Hence, the expected value of $u_{i,t}$ becomes $(a + \phi(1)\delta)$ under the stationary alternative in the long run after the break date. As suggested by Perron and Vogelsang (1992), models (2.5) and (2.6) can be nested and approximated by the finite-order autoregressive model

$$u_{i,t} = \mu + \delta DU_t + \theta D(TB)_t + \rho u_{i,t-1} + \sum_{j=1}^{k} \varsigma_j \Delta u_{i,t-j} + \varepsilon_{i,t}, \qquad t = k+2, ..., T \tag{2.7}$$

Similarly to the augmented Dickey-Fuller regression, lags of first-differences, $\Delta u_{i,t-j}$, are included on the right-hand side of the equation. Model (2.7) can be estimated by OLS. Under the null hypothesis of a unit root, the autoregressive

[14] This finding is also in line with the general remark of Hansen (2001), who argues that a structural break is unlikely to be immediate. Nonetheless, we also tried the AO model, but as expected, its performance turned out to be inferior compared to the IO model. This means that the AO model rejects the null hypothesis in fewer cases.

parameter $\rho$ is equal to 1, which implies $\delta = \mu = 0$ if there is no time trend.

Since we do not specify the break date $T_b$ beforehand, we need an empirical strategy to estimate $T_b$ along with the other parameters of (2.7). For this estimation, there are two options. Under both options, one first performs regression (2.7) for all possible breaking dates. Then, under the first option, the break date is chosen to minimize the $t$-statistic on $(\rho - 1)$. In other words, this option selects the break date to provide most evidence against the random walk hypothesis.

The alternative option identifies the break point as the value of $T_b$ that maximizes the $t$-statistic (in absolute terms) on the coefficient associated with the change in the mean, $\delta$. In other words, this option chooses the break date to capture the most significant change in the series.

Perron and Vogelsang (1992) derive asymptotic distributions of the test statistics and finite-sample critical values for typical sample sizes. In order to obtain critical values that correspond exactly to our sample size of $T = 43$ and a maximum lag length of $k_{\max} = 8$, we perform 5000 replications of a Monte-Carlo experiment to simulate the unknown distribution of $\rho$. There are various procedures to select the appropriate order $k$ of the estimated autoregressions and each procedure influences the distribution of $\rho$ under the null hypothesis. Most prominent procedures are Ng and Perron's (1995) sequential $t-$test, Akaike's information criterion (AIC), and the Schwartz-criterion (BIC).

### 2.5.2 Test results

Table 2.6 summarizes the results of the Perron and Vogelsang (1992) unit-root tests obtained by minimizing the $t$-statistic on $(\rho - 1)$ over all possible break points. The augmentation lag length has been determined by using sequential $t-$tests.

In seven out of ten cases, we are able to reject the null hypothesis of a unit root in favor of regime-wise stationarity at least at the 10 percent level of significance. Recall that the univariate unit-root tests without structural breaks rejected the random walk hypothesis only for one federal state. For three of the ten federal states we still cannot reject the null hypothesis of a random walk even after accounting for a structural break. These states are Baden-Wuerttemberg, Niedersachsen, and Schleswig-Holstein. However, the non-rejection seems to be due to a lack of power as point estimates for $\rho$ range from 0.5 to 0.7. The weak power of the test can also be seen if we look at the opposite extreme cases. Although the estimates of $\rho$ for Bremen and Hessen are virtually zero, the test rejects the hypothesis of $\rho = 1$ only at the 5 or even 10 percent level of significance. However, we do not need to worry too much about a potential problem of low power, because we are in fact able to reject the null hypothesis in seven out of ten cases. If the power problem were effective in our sample, a potential way to increase the power would be to exploit the panel dimension again.

The data-dependent choice of the break date mostly coincides with the a priori assumption that the second oil crisis and the following recession had a huge and persistent impact on relative unemployment rates. For all but three series, the chosen break date falls into the period of 1978-1982.

The three states for which the estimated break date falls outside this period are Rheinland-Pfalz, Hessen, and Schleswig-Holstein. For Rheinland-Pfalz, the ADF test without structural break already rejected the unit root. For Schleswig-Holstein, the estimated break date coincides with the first oil crisis, but the unit root cannot be rejected. Only for Hessen, the break date is hard to interpret. It could be German reunification of 1989/90 that affects Hessen with a three year time-lag in 1993. But since we cannot give a clear-cut explanation for the break date in economic terms, we may view the test results for Hessen—including the rejection of the unit root—with reservation.

The unemployment rate for Germany as a whole remains non-stationary even after accounting for a structural change in the level. This result is in line with the findings of Papell, Murray, and Ghiblawi (2000).[15]

These results are relatively robust with respect to the two different methods to determine the break point. The two methods do lead to different estimates of break-points and/or a different number of augmentation lags in only two cases. For Niedersachsen, the alternative $\delta-$method estimates the break point to be 1979 instead of 1978 without a change in the qualitative result of non-stationarity. For Rheinland-Pfalz, the $\delta-$method yields 8 augmentation lags and can no longer reject non-stationarity. However, this again reflects low power as we could already reject non-stationarity for Rheinland-Pfalz using the ADF test.

Although Perron and Vogelsang (1992) recommend sequential $t$-testing, we check the robustness of the results to alternative methods of lag-length selection. Both, the AIC and the BIC tend to choose shorter lag length than sequential

[15] Papell, Murray, and Ghiblawi (2000) analyze hysteresis in OECD unemployment rates. They adopt unit-root tests with multiple structural breaks and show that the West German unemployment rate is non-stationary.

Table 2.6: Perron and Vogelsang unit-root tests, lag length selected by sequential t-tests

**Perron and Vogelsang (1992) test**

| Fed. State | $T_b$ [1] | $k$ [2] | $(\hat{\rho}-1)$ | $\hat{\delta}$ | Fed. State | $T_b$ [1] | $k$ [2] | $(\hat{\rho}-1)$ | $\hat{\delta}$ |
|---|---|---|---|---|---|---|---|---|---|
| BW | 80 | 6 | -0.51 | -0.69 | NRW | 80 | 6 | -0.72** | 0.78 |
| | | | (-4.23) | (-3.76) | | | | (-5.54) | (5.05) |
| BY | 81 | 5 | -0.70** | -1.08 | RP | 70 | 0 | -0.62* | -0.36 |
| | | | (-5.03) | (-4.81) | | | | (-4.72) | (-2.75) |
| BRE | 82 | 5 | -0.95** | 3.75 | SAAR | 78 | 2 | -0.59** | 2.06 |
| | | | (-4.99) | (4.78) | | | | (-5.21) | (4.56) |
| HH | 82 | 1 | -0.73** | 1.75 | SH | 72 | 0 | -0.40 | 0.39 |
| | | | (-5.22) | (4.96) | | | | (-3.36) | (2.37) |
| HE | 93 | 4 | -0.95* | 0.75 | $ur_{Ger}$ | 79 | 6 | -0.35 | 1.94 |
| | | | (-4.60) | (3.57) | | | | (-3.67) | (3.53) |
| NS | 78 | 2 | -0.31 | 0.27 | | | | | |
| | | | (-3.51) | (2.30) | | | | | |

| Critical Values[2,3] | 1% | 2.5% | 5% | 10% |
|---|---|---|---|---|
| $T_b$ chosen by min. $t_{(\hat{\rho}-1)}$ [1] | -5.61 | -5.25 | -4.91 | -4.53 |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively. $t$–statistics in parenthesis.

[1] $T_b, k, \rho, \theta$ are obtained by minimizing the $t$-statistic on $(\hat{\rho}-1)$.

[2] Lag length $k$ chosen according to a significance test on the last included lag, given a pre-specified maximum of $k = 8$.

[3] Obtained from the empirical distribution of 5000 replications of a Monte Carlo experiment.

$t$-testing, but the estimated break points remain very similar.[16]

Only for Hessen, we cannot reject the unit root on the basis of an information criterion, but could reject the unit root under sequential $t$-testing.[17] This confirms our previous warrant concerning the test results for Hessen for which the estimated break date was not intuitive.

Also the results for Bayern and Bremen change under the AIC and BIC, but only quantitatively. The levels of significance pejorate somewhat (from 5% to 10% level). However, this is only due to a marginal change of significance from below 5% to slightly above this level. This can be illustrated by plugging-in the estimated $t$-values in the simulated distribution obtained by the Monte-Carlo experiment. For the BIC, for example, we get approximate $p-$values of 6.2% and 5.4% for Bayern and Bremen, respectively.

To further test the robustness of our results, we also tried unit-root tests which allow for a break both in the intercept and in the trend (Perron, 1997, Zivot and Andrews, 1992). Allowing for breaks in the time trend provides little additional evidence against the unit-root hypothesis. The unit-root hypothesis cannot be rejected at a higher level of significance because the power of the tests declines when unnecessary breaks are included.

### 2.5.3 Speed of convergence

It has been the moderate speed of convergence, which we have inferred from the panel-based unit-root tests, that has motivated us to apply a test which allows for a structural break. To show that the estimated speed of convergence is substantially affected by the structural break, we analyze the half-life of a shock to relative unemployment rates implied by the results of the Perron and Vogelsang (1992) test. This, of course, makes sense only for those regions for which non-stationarity could be rejected. For those states for which the unit-root hypothesis cannot be rejected, shocks have a persistent effect and the implied half-life is infinite.

For those series which are found to be stationary by the Perron and Vogelsang (1992) regressions, we generate a moving-average representation of the estimated autoregressive process that includes the augmentation lags. This moving-average representation is used to compute impulse-response functions and we define the half-life of a shock as the date at which the initial impulse

[16] Detailed results are presented in Appendix A.

[17] The lag-length selection criterion influences the distribution of the $t$-statistics under the null hypothesis of non-stationarity. Therefore, we have simulated the distributions for each criterion by Monte-Carlo experiments.

Table 2.7: Half-lifes (in years) of shocks to relative unemployment rates, computed from impulse-response functions based on regression results as reported in Table 2.6

| Federal State | BY | BRE | HH | HE | NRW | RP | SAAR |
|---|---|---|---|---|---|---|---|
| Half-life | 2 | 1 | 2 | 1 | 3 | 1 | 1 |

Note: Three federal states are omitted, for which the relative unemployment series were found to be non-stationary.

has lost at least half of its effect for the first time.

The estimated half-lifes are reported in Table 2.7. While the implied half-life is 5.6 years when the results of the LLC test are used, the half-lifes go down to between 1 and 3 years when we include a structural break. Consequently, measured persistence is substantially biased upwards if the structural break is omitted.

## 2.6 Interpretation and discussion

Although it is hard to fix a clear theoretical underpinning for our finding of regime-wise convergence, a potential explanation could be hysteresis.[18] As a theory, hysteresis usually refers to the absolute levels of unemployment and is associated with the existence of multiple equilibria. The multiple equilibria manifest in non-linear, non-stationary behavior of unemployment, which displays a high degree of persistence in turn, e.g. unit-root or close to unit-root behavior.[19] Instead of testing for high persistency, a more direct approach were a test for structural breaks which represent endogenous shifts from one equilibrium to the other, as for example in the 'coconut' model of Diamond (1982).

However, Amable et al. (1991) and Cross (1994) have challenged the latter strategy building on the ideas of Krasnosel'skii and Pokrovskii (1989) and Mayergoyz (1991). They point out that it also depends on the degree of heterogeneity at the micro level, whether hysteretic micro behavior manifests itself

[18] We thank an anonymous referee for suggesting this link.

[19] See Blanchard and Summers (1986), Roed (1997), Amable et al. (1994), Amable et al. (2005).

in structural breaks at the macro level, or in more general forms of non-linear persistent time-series behavior. If the hysteretic forces are heterogeneous at the micro level, aggregate behavior is smooth, but non-linear and persistent. If there is homogeneity at the micro level, however, hysteresis should result in structural breaks. In any case, hysteresis implies that the distribution of relative unemployment rates is not stable over time.[20]

We do find evidence for a change in equilibrium following the second oil crisis. Our test results overall—low persistency with structural breaks and high persistency without structural breaks—may thus suggest some form of hysteresis driving relative unemployment rates in West Germany, if microeconomic agents are relatively homogeneous with respect to their employment decisions ('strong macroeconomic hysteresis', see Cross, 1994 and Amable et al., 1991).

An alternative explanation for these patterns would be a permanent shift of exogenous parameters that determine the equilibrium (Roed, 1997, p. 394) instead of an endogenous change from one equilibrium to the other as proposed by hysteresis theory. Whether the change in equilibrium forms endogenously or is due to an exogenous and permanent shift of deep parameters can hardly be discriminated on the basis of our univariate analysis.[21]

Although the literature has typically stressed the difference between exogenous change and hysteresis (Roed, 1997, p. 406), both have similar implications for regional policy against the background of our results. Irrespective of how one motivates the permanence of the change in the 1980s structurally, one can expect small government interventions to loose their effect quickly. We find that relative unemployment rates adjust quickly to their equilibrium levels, but in exceptional cases the economy might move from one equilibrium to the other. Consequently, a policy intervention needs to take the form of a substantial intervention or a substantial change in politically set parameters in the case of hysteresis or structural change, respectively.

The question whether hysteresis or structural change is driving our results, hence, determines merely the aim and the means of the substantial policy intervention. It has no influence on the suggested size of the intervention, which has always to be substantial to be effective. We cannot tell which policies are actually likely to reduce relative unemployment dispersion, but most policies

[20] Belke and Göcke (2005) extend this argument to the role of uncertainty in hysteresis. For a survey, see Göcke (2002), which provides an overview of the concepts of hysteresis and their implications for applied economic studies.

[21] A possible way to discriminate would be to analyze the employment behavior at the micro and macro level simultaneously, but this data is not available for the long period of time we want to study.

that aim at reducing relative unemployment differences are unlikely to make permanent contributions to social welfare because they are simply to small.

One might argue that this conclusion is misleading since we ignore the endogeneity of regional policy. Such policy endogeneity may result in mean-reverting behavior of relative unemployment rates although these rates would be non-stationary in the absence of regional policy. In such setting, regional policy in fact contributes substantially to social welfare by stabilizing the economy and our conclusion above would be just turned on its head.[22]

However, this more optimistic view of regional policy has a hard time to explain why we only find conditional convergence with a structural break. If regional policy were indeed fully effective in reducing the dispersion of unemployment, then one would expect that policy were able to eliminate regional differences completely. In other words, one would have to construct complicated reasoning to justify why the aim of policy should be to obtain an equilibrium dispersion of unemployment in which some states have permanently higher unemployment rates than others. Moreover, this reasoning would need to explain why this dispersion changed in the 1980s. One such explanation could be different costs of regional employment policy. That is, jobs are permanently attracted more cheaply by government intervention in the low unemployment states, e.g. Bayern. However, in this case it must be that the marginal costs of job attraction have changed after the second oil crisis for some states, but not for others. Overall, we find this explanation less intuitive than the simple presumption that regional employment policy cannot permanently attract jobs unless it changes significantly the fundamental economic parameters.

Consequently, this leads us to conjecture that the stabilizing effect of (small but constant) policy interventions must be limited even taking into account the problem of policy endogeneity. Nonetheless, we may arrive at a more qualified result with a deeper analysis using more detailed multivariate data or microdata. Yet, for Germany, there is no longitudinal microdata of which the time-span is large enough to cover the second oil crisis. Also at the regional level, there is hardly data that may help to shed more light on the issue of policy endogeneity and covers our sample period from 1960 until 2002.

[22] We thank an anonymous referee for pointing this out to us.

## 2.7 Conclusion

The question of this paper was whether there are forces that lead to convergence in the levels of regional unemployment rates over time. We used German regional data on unemployment aggregated from the Mikrozensus database covering the period 1960-2002 and performed univariate as well as panel unit-root tests to examine the hypothesis of stochastic convergence. On the basis of univariate ADF tests the hypothesis of non-convergence cannot be rejected. But using more powerful panel unit-root tests, we found some evidence for conditional convergence in regional unemployment rates. They converge up to a stable equilibrium distribution. Yet, the panel-based tests imply a moderate speed of convergence at best.

Since the graphical analysis of the series suggested the presence of a shift in the equilibrium differential of regional unemployment rates after the second oil crisis, we extended the convergence tests to allow for such a shift. We employed the univariate unit-root test of Perron and Vogelsang (1992) that includes a level shift in the series analyzed. In contrast to the univariate ADF test, the non-convergence hypothesis could be rejected for seven out of ten federal states. Moreover, the estimated speed of convergence increased substantially in comparison to the results of the panel-based tests. Consequently, regional unemployment rates are found to converge quickly to a constant difference to the national average, but this difference is not the same for the two regimes before and after the second oil crisis.

On the side of the econometric analysis, our paper, like many others, provides once more evidence of the low power of univariate tests in small samples. This problem is especially apparent in the setting with a structural break and we have dealt with it in two ways: including the panel dimension and accounting for the structural break.

The structural break following the second oil crisis reveals the importance of using for our analysis a database that spans a long time-frame. While a shorter series of higher frequency, e.g. monthly data, may be more powerful to quantify the exact speed of convergence in the absence of structural breaks, it would be unable to uncover structural change itself. We have seen the importance of structural breaks for both, the empirical results and their interpretation. For example, structural breaks may allow us to discriminate between different types of hysteresis.

In turn, the finding of structural breaks has important implications for policies targeted at regional unemployment rates. If there is regime-wise conditional convergence and fast equilibrium adjustment, then this implies on the one hand that small government interventions loose their effect quickly as unemployment rates adjust back to their equilibrium levels. On the other hand, the result means that large interventions might move the economy from one equilibrium to the other. Hence, policy intervention needs to take the form of a substantial regime shift.

# Chapter 3

# A Distribution Dynamics Approach to Regional GDP Convergence in Reunified Germany

## 3.1 Introduction

This paper presents an empirical study of GDP per worker convergence across German labor market regions during 1992 to 2002 using nonparametric techniques. The nonparametric methodology originally introduced by Quah (1993, 1996a, b, c, 1997, 2001) studies how the *entire* cross-sectional distribution of relative GDP evolves over time and is therefore not limited to an analysis of single moments of the underlying distribution as it is the case for traditional $\beta$- and $\sigma$-convergence approaches. Further advantages of the empirical strategy used in this paper are that growth and distribution are considered jointly and that it allows for an out-of-sample extrapolation of the observed distribution dynamics. Our extrapolation exercise follows recent developments in the convergence literature as proposed by Johnson (2000, 2005) and others.

The convergence hypothesis states that poor economies catch up with rich ones. This topic is important for Germany because mitigating regional disparities is regarded as a fundamental objective of German (and European) policy, especially in light of East-West differentials in reunified Germany. At the heart of the debate about regional inequality stands a fundamental controversy about whether or not a process of economic homogenization has taken or will take place in reunified Germany.

This study uses GDP data to contribute statistical evidence to the debate about regional inequality in Germany. One reason to focus on convergence in GDP is that policy does formulate its aims with respect to GDP. For example, the main objective of EU regional policy is to promote the development of regions whose per capita GDP is below 75% of the EU average and approximately 70% of total EU regional expenditure is spent for making regions more equal in terms of output (Overman and Puga, 2002).[1]

In order to mitigate regional disparities in GDP, disadvantaged regions in Germany are allocated funds from the European Structural Funds and the German 'Gemeinschaftsaufgabe Verbesserung der regionalen Wirtschaftsstruktur' (GRW). The GRW is the guideline for German regional policy and advocates a supply-side policy supporting growth in order to eliminate regional differences. For the allocation of subsidies the GRW has defined 271 regional labor markets. This paper addresses GDP convergence at the level of these labor market regions.

Ideally, we would analyze convergence of real GDP. Unfortunately, data limitations prevent us from calculating output measures adjusted for cost-of-living, a shortcoming which also applies for most studies on regional convergence in other countries. Nevertheless, we believe that the present study provides important insights for assessing the development of the regional GDP distribution in reunified Germany.

A particular feature of the approach taken in this paper is that it allows one to make predictions about the long-run distribution of regional GDP. This is an important aspect because it gives a rough estimate about the long-term outcome *given* that the convergence process remains the same over time. Using the more technical terminology of the distribution dynamics approach, we investigate what will happen to the German regional GDP per worker distribution if the observed distributional dynamics remained unchanged.

The main results of this study are the following. There is evidence for a tendency towards convergence during the period we study, i.e. regions that were less productive in 1992 have a higher relative GDP in 2002. The convergence process is driven mainly by the catching up of East German regions in relative terms.

Concerning the long-run distribution of regional GDP, however, this study provides discouraging evidence. The ergodic density we calculate on the ba-

[1] Since 1994, the East German federal states (excluding East-Berlin) are objective 1 development areas and they will receive subsidies totalling 19.229 million Euro until today (Eckey, 2001).

sis of our estimates is characterized by pronounced polarization. This finding illustrates that it is unlikely that German labor market regions will converge towards equality in terms of GDP per worker. Rather, there are two basins of attraction in the long-run distribution of regional GDP, one at a GDP per worker close to the national average value and one at a significantly lower level (73% percent of the German-wide average). A separate analysis of the West and East German economies provides evidence that the polarization in the long-run GDP per worker distribution reflects a long-term heterogeneity among West and East German regions.

Overall, the analysis reveals a tendency towards convergence on the one hand but also persistent polarization between the GDP per worker of East and West German regions on the other hand. This means that there clearly has been a catching-up process during the past period we can observe. But this catching-up process does not result in a unimodal distribution of GDP per worker in the long run. Rather, the distributional dynamics manifest themselves as polarization if these dynamics continue operating unchanged in the future. That regional inequality in GDP per worker is likely to persist rather than decrease in the future is an alarming result which is of particular importance against the background of substantial regional policy expenditures taken in the last decade.

The remainder of this paper is organized as follows. The literature is briefly discussed in Section 2. Section 3 introduces the data employed. The empirical analysis is presented in Section 4 and the last section concludes. Technical details of the estimation procedure are presented in Appendix B.

## 3.2 Literature

As for most other regional convergence studies, the theoretical framework of the empirical analysis is the neoclassical growth model which suggests that regional per capita output within a country converge to the same long-run steady-state (see Magrini, 2004 and Durlauf, Johnson, and Temple, 2005 for recent surveys of the large literature). However, regions are by no means small closed economies but instead are highly integrated in terms of mobility of goods, capital, and labor. Hence, in a regional context the neoclassical growth model for closed economies does not appear to be the best framework for convergence studies. Barro, Mankiw, and Sala-i-Martin (1995) have extended the neoclassical growth model for partial factor mobility and show that the basic prediction of convergence is not altered in this setting. For an elaborate analysis of the role of labor mobility in the convergence process we refer to Razin and Yuen (1997). By contrast, new theories of industrial location, trade, and integration (see Fujita, Krugman, and Venables, 2000) and most models of the new growth theory cast doubts on the neoclassical optimistic prediction of convergence.

While it is quite clear in theory what economic convergence means, empirical measurement of convergence is not a trivial task. In recent years, a number of alternative strategies have been suggested, e.g. traditional cross-sectional regressions of $\beta$- and $\sigma$-convergence, panel data models, and time-series tests (see the review of Magrini (2004) for a survey focusing on regional convergence studies).

There are several studies which apply these techniques to analyze regional convergence in West Germany and in general, the studies do find evidence for both, absolute and conditional convergence. Empirical evidence regarding reunified Germany is still scarce. A potential reason for this has been pointed out by Kosfeld, Eckey, and Dreger (2002) who state that regionally disaggregated data on economic growth have only recently become available.

Most studies for reunified Germany are limited to an analysis of convergence between the Eastern and Western part of the country.[2] Although some authors are more pessimistic than others about convergence, the general result is that 'East German labor productivity has converged on that in West Germany more slowly than was initially thought but faster than would have been expected on the basis of studies of convergence such as Barro and Sala-i-Martin (1991)' (Barell and te Velde, 2000, p. 272).

Our paper is a contribution to the literature which addresses regional convergence in reunified Germany at a disaggregated geographic level. Using a spatial econometric approach to $\beta$-convergence, Kosfeld, Eckey, and Dreger (2002) find clear evidence for both, GDP per capita and labor productivity convergence during the period 1992 to 2000. Kosfeld and Lauridsen (2004) adopt a cross-sectional spatial econometric adjustment model which is based on the concept of spatial error-correction. They find only weak evidence for conditional convergence in the year 2000.

One shortcoming of the $\beta$-convergence approach is that, by focusing on the average behavior of a representative region, it suppresses the cross-section dynamics one wishes to investigate (see Quah, 1996a, b, c, 1997). This criticism also holds for spatial econometric extensions of the $\beta$-convergence approach.

[2] See Hallett and Ma (1993), Burda and Funke (1995), Funke and Strulik (2000) and Barrell and te Velde (2000).

One possibility to overcome the limits of the $\beta$-convergence method is to estimate the entire GDP distribution and its dynamics over time. Only this method allows one to uncover empirical phenomena such as persistence and the formation of convergence clubs. Since pronounced East-West disparities are a well-documented fact in reunified Germany (see Barell and te Velde, 2000), it appears promising to adopt the distribution dynamics approach to Germany, which has not been done yet in the literature.

## 3.3 Data

Germany's official statistics provide GDP data for disaggregated administratively defined regions (counties). A regional economic analysis based on these county data can be misleading because the borders of German counties are determined by political and historical rather than economic reasons. Therefore, we aggregate counties to so-called local labor market regions, which are the target areas for the most important regional policy program in Germany, the GRW. We use data for 439 German counties to define 271 labor market regions, so that center and hinterland of labor markets are adequately integrated on the basis of commuter flows.

Empirical growth studies use either GDP per capita and/or GDP per worker as a dependent variable. Since most theoretical growth models are based on production functions, their implications relate more closely to GDP per worker than GDP per capita (Durlauf, Johnson, and Temple, 2005). In general, GDP per worker is a more accurate index of average labor productivity than GDP per capita. Moreover, at a disaggregated regional level, GDP per capita data are less informative than their per worker equivalents due to possible distortions caused by commuter flows. If workers live in one region and commute to work in another region, the GDP per capita variable is subject to a bias because GDP is measured at the workplace while population data refer to the place of residence.[3] By contrast, data on total employment refer to the workplace at which GDP is measured. For these reasons, we focus on GDP per total employment, i.e. GDP per worker.

The raw GDP data at the county level are taken from the National Accounts of the Federal States compiled by the Statistical State Office Baden-Wuerttemberg and are measured in current prices. Regional price indices at the county level or at the level of labor market regions are not available. Total

[3] The aggregation of counties to labor market regions picks up only the most important commuting linkages.

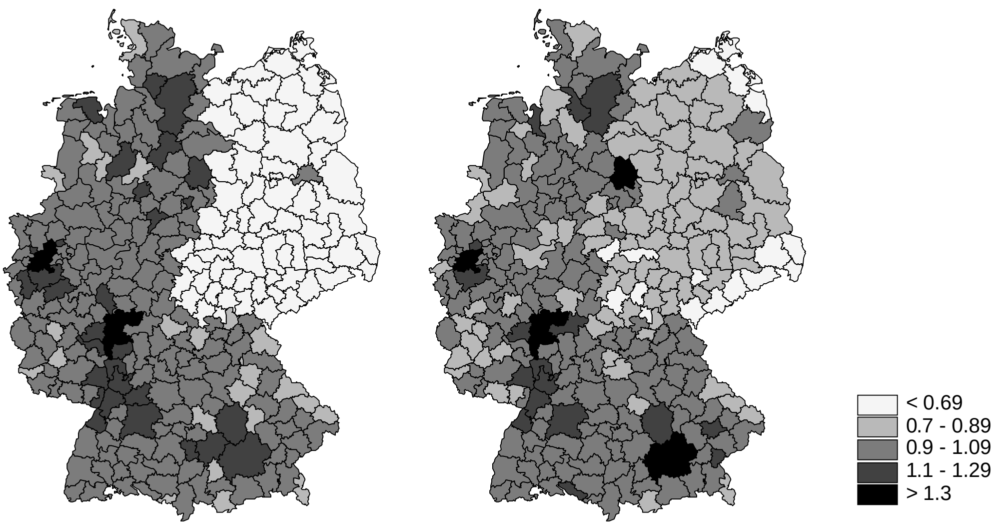


Figure 3.1: GDP per worker across German labor market regions, relative to the German-wide average GDP per worker. Left: 1992, right: 2002.

employment data are reported by the Federal Office for Building and Regional Planning. The time period under study ranges from 1992 to 2002.[4]

The key variable in our econometric analysis is relative GDP per worker, which means that regional GDP per worker data are normalized by the labor force weighted national average GDP per worker. This normalization allows us to abstract from the growth of the German economy during the period under study and it also accounts for common changes in inflation. It should be noted that the distribution of relative GDP per worker has the same shape as compared to the distribution of GDP per worker itself.

Our estimations are based on data for all regions. Potentially outlying data points represent regions which performed either extremely well or poor and from an economic point of view it is not appealing to simply delete these observations (Quah, 1997). As a robustness test, however, we will check if the estimated distributional dynamics are heavily affected by potentially outlying data points. It turns out that this is not the case. The complete sample consists of 271 German labor market regions which are observed for 11 years.

As a starting point, we document regional disparities in relative GDP per worker, for 1992 and 2002. Figure 3.1 illustrates the apparent East-West disparities in reunified Germany. It is instructive to compare relative production

[4]There are no data for 1993. In the empirical analysis, it does not make a significant difference whether we exclude the year 1993 or linearly interpolate the data for 1993.

in labor market regions with extreme values. The average relative GDP in the ten most productive regions is 1.31 in 1992 and 1.28 a decade later. The ten least productive regions have an average of only 0.45 in 1992 and 0.65 times the German average in 2002. These numbers clearly illustrate that regional disparities are still very pronounced in reunified Germany but they also suggest that a certain amount of catching up has taken place.

In order to get a first impression of the dynamics of regional inequalities we ranked the regions in descending order in terms of their 1992 positions. Then, we calculated the Spearman rank correlation coefficient in order to assess if the position in the league table of GDP in 1992 is a good predictor of that position in 2002. The coefficient takes a value of 0.86 (significant at the 1% level) indicating that the dominant pattern is persistence but there is also some mobility in relative positions.

In the remainder of this paper it is analyzed if regional disparities in production continue to persist, particularly if they do so after a decade of substantial regional policy expenditures.

## 3.4 Empirical analysis

In a first step of the empirical analysis we estimate density functions of relative GDP per worker for different years. By evaluating whether unimodality in the densities of the distributions is present or not, this procedure is a test of the convergence hypothesis. For example, if one starts with a bi- or multimodal density at a given point in time (e.g. a group of very productive and a group of less productive regions), convergence would imply a tendency of the distribution to move towards unimodality (Bianchi, 1997).

In a second step we estimate transition probabilities to analyze mobility within the GDP distributions. We examine how a given individual of the distribution at a given point in time transits to another part of the distribution in the future. In other words, we analyze if regions move up or down in the ranking of GDP per worker.

Thereafter, we calculate the ergodic or invariant density of relative GDP per worker implied by the estimated transition probabilities. This exercise of out-of-sample extrapolation allows us to make long-run predictions on the GDP distribution in reunified Germany.

### 3.4.1 Density functions of relative GDP

Nonparametric kernel techniques (see Silverman, 1986 and Pagan and Ullah, 1999) are used to analyze the shape of the distribution of German relative GDP for two different years, 1992 and 2002. One advantage of the nonparametric approach is that one does not have to assume any particular form about the density shape because the densities are estimated from the data. These estimated densities can be interpreted as the continuous equivalent of a histogram, where the number of intervals tends to the continuum.[5]

A crucial point in nonparametric econometrics is the choice of the bandwidth. The larger the value of the bandwidth, the smoother is the density estimate. Besides the problem of choosing the most appropriate bandwidth, further problems may arise if the bandwidth is assumed to be fixed over all data points. It can be shown that an estimation with fixed bandwidth may result in undersmoothing in areas with only few observations and in oversmoothing in others. This means that kernels estimated using a fixed bandwidth are heavily affected by noise in regions of low density and are otherwise unable to detect all distribution details in regions where data concentrate. In particular, these problems arise if the underlying density is multimodal. Since the German GDP distribution is possibly characterized by multiple modes (e.g. East and West), we employ nonparametric techniques which allow for a varying rather than fixed bandwidth.

Such kernel techniques with flexible bandwidth are called adaptive kernels (see Silverman, 1986 and Pagan and Ullah, 1999). An adaptive kernel estimator adapts to the sparseness of the data by varying the bandwidth inversely with the density. This means that a broader bandwidth is used for observations located in regions with low density, and vice versa. Thus, adaptive kernels are able to recover more details of the density where data concentrate because the window width decreases at those regions while it increases in areas of only low data densities.

A two-step procedure is used to estimate adaptive kernels. First, an initial (or pilot) estimate of the probability density function with fixed bandwidth is computed. This pilot estimate is used to evaluate whether an observation is located in a region of comparatively low or high density. The adaption of the bandwidth for each sample point is computed by multiplying the fixed pilot bandwidth with so called local bandwidth factors (for technical details we refer

[5] The following brief discussion of adaptive kernel methods is based on the overview in van Kerm (2003).

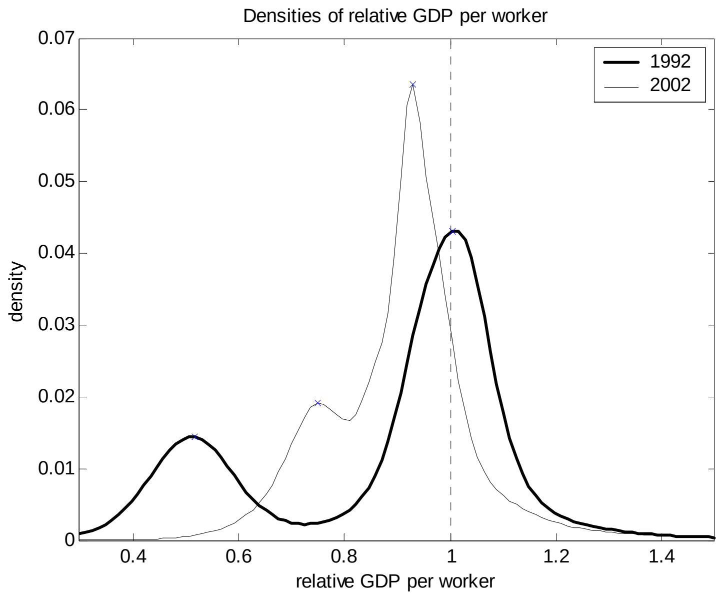


Figure 3.2: Densities of relative GDP per worker across 271 German labor market regions, 1992 and 2002.

to Appendix B.1).

Still an open question is how to select the bandwidth of the pilot estimate. Among several possibilities to select, we choose the smoothing parameter using Silverman's (1986, Section 3.4.2) rule of thumb. Specifically, we use the adaptive rule of thumb. In order to check the robustness of our results with respect to the bandwidth criterion, we alternatively employ the Sheather and Jones (1991) *plug-in* method for the estimation of our final specification in Section 3.4.4.

Figure 3.2 shows the density functions of relative GDP per worker for the initial and final year of the sample period estimated using a Gaussian kernel. The densities have been normalized so that the sum of the points at which the density is evaluated is one. This allows us to interpret the normalized densities as showing the probability of a realization in the grid interval.[6]

In 1992, the GDP distribution is clearly bimodal. The first mode is at a relative GDP of 0.52 and the second mode coincides with average GDP per worker (1.00). Hence, regions in the productive cluster have twice the GDP per worker of those in the other group.[7] We suppose that the cluster of less

[6] All computations in this paper were performed using MATLAB.

[7] One could perform bootstrap multimodality tests as in Bianchi (1997) to formally test for two peaks, but we believe the figure speaks for itself and there are no doubts about the presence of *exactly* two peaks.

productive regions in 1992 is mainly formed by regions located in the new federal states because of their low GDP levels after German reunification. This issue will be addressed below.

A decade later, in 2002, the density has changed substantially. The two peaks of the distribution correspond to 0.75 and 0.93 times the German GDP per worker. Possibly, the left peak is not a significant mode in the distribution anymore. That much is certain, there is considerably weaker evidence for a clustering of less productive regions in comparison to 1992. It seems as if most unproductive regions have increased their relative GDP. The apparent tendency towards convergence is reflected by the distance between the peaks, which decreases from 0.48 in 1992 to 0.18 in 2002.

To illustrate further the convergence between German labor market regions, we compare the standard deviations of the two density functions. If there is convergence, the dispersion of the density should decline over time. In 1992, the standard deviation is 0.236 and it decreases to 0.138 a decade later, indicating that the relative GDP per worker distribution has become more equal over time.

Since we suppose that the observed tendency towards convergence in reunified Germany is primarily driven by the catching-up process of East German regions, it is instructive to analyze the shapes of the GDP distribution for West- and East German regions separately. This experiment allows us to assess if there is also convergence within the Western part of Germany.

Figure 3.3 shows the kernel-smoothed densities of relative GDP per worker for the Western and Eastern part of Germany separately.[8] We evaluated the densities for West and East German regions at the same values, so that the two graphs can be compared in one figure.

Consider first the densities of East German GDP per worker. In 1992, the peak of the distribution is at 52% of the German average. As expected, this mode corresponds to the left peak in the distribution of all German regions as displayed in Figure 3.2 and provides evidence that the cluster of unproductive regions in Figure 3.2 is mainly formed by East German regions. In 2002, the whole distribution has shifted to the right; the peak is now at 74% of the German average. These numbers illustrate that, although East German labor market regions have increased their relative GDP per worker over time, they still have considerably lower levels of GDP per worker than the national average. This finding is well compatible with other studies, such as Barell and te Velde

[8] There are 205 West German and 66 East German labor market regions. Berlin is treated as a West German region.

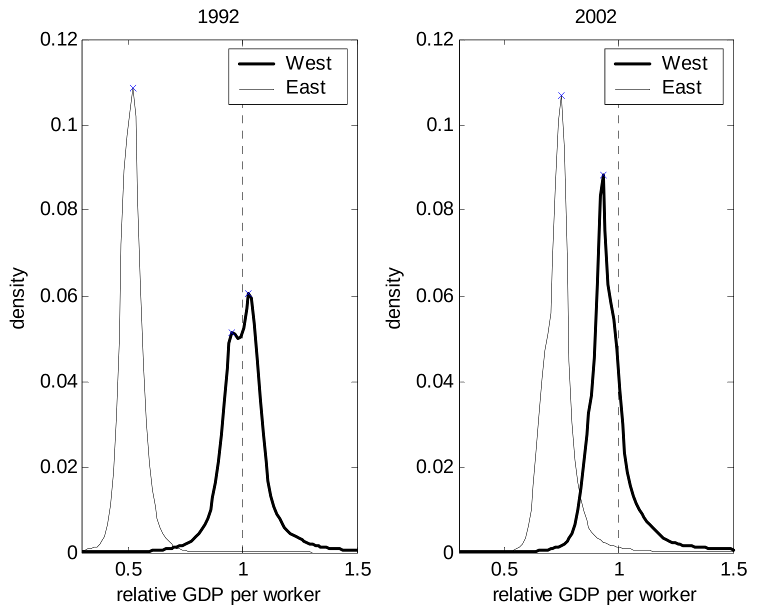


Figure 3.3: Densities of relative GDP per worker for West- and East German regions separately, 1992 and 2002.

(2000).

While the location of the entire density of East German regions has shifted to the right without changing its external shape, the density shape of West German regions has changed over the ten-year horizon. There is evidence for a reduction of disparities across West German regions, as indicated by the bimodal density in 1992 which has changed to a unimodal density in 2002. In 1992, the peak with the highest density corresponds to 1.02 times the German average and it decreases to 0.93 in 2002. Nearly the same peaks were obtained for the GDP distribution of all German regions as displayed in Figure 3.2. This confirms the presumption that the West German regions cluster together in the center of the distribution of all German regions.

The results of this section suggest that there has been a tendency towards convergence across German labor market regions during the past period we can observe. The convergence process, however, is not finished in 2002 and there are still substantial regional disparities, especially between the East and the West. The question arises if the past tendency towards convergence actually manifests itself in the future as long-term convergence towards a unimodal GDP distribution. This question is investigated in the next two sections.

### 3.4.2 Intradistribution mobility

Thus far, we have analyzed the shapes of relative GDP distributions for two different years. Obviously, the densities have fluctuated but we could not say anything about movements of individual regions in the distribution. However, for describing convergence it is important to have information on how regions move within the distribution. Generally, a broad range of such intradistribution mobility is possible, for example, over time some initially rich regions fall behind; poor regions overtake rich ones; and groups of regions, beginning at similar levels of development, eventually diverge (Quah, 1996a).

In this section we analyze intradistribution mobility by estimating a probability model of transitions which captures the distribution's law of motion (see Quah, 1993, 1996a, b, c, 1997). This means that we examine how a given individual of the distribution at time $t$ (e.g. 1992 or some other year) transits to another part of the distribution by the time $t+\tau$ (e.g. 2002).

One possibility to examine transition probabilities is to discretize the GDP space and then count the observed transitions out of and into distinct discrete cells of a Markov transition probability matrix (Quah, 1993). However, Bulli (2001) has shown that an arbitrary discretization of the state space alters the probabilistic properties of the data. A better approach is to use no discretization but instead allowing the number of cells of the Markov transition probability matrix to tend to infinity (Quah, 1997). In this continuous case, the transition probability 'matrix' becomes a stochastic kernel. Such a kernel is a huge non-negative matrix whose rows integrate to unity, satisfying regularity conditions to ensure that a limiting distribution exists (Quah, 2001).

Assuming that the process describing the evolution of the distribution is time-invariant and first-order Markov, the relationship between two distributions at different points in time can be written as[9]

$$f_{t+\tau}(z) = \int_0^\infty g_\tau(z|x) f_t(x) dx, \tag{3.1}$$

where $g_\tau(z|x)$ is the $\tau-$period ahead density of $z$ (e.g. GDP today) conditional on $x$ (e.g. GDP in some base year). The stochastic kernel $g_\tau(z|x)$ encodes all information about the evolution of the sequence of distributions over time and maps the distribution from period $t$ to period $t+\tau$. The kernel is a conditional density and shows the probability that a given region transits to a certain state

[9] This simplified presentation of Quah's (1997) methodology was proposed by Johnson (2000, 2005). It can also be found in Durlauf, Johnson, and Temple (2005).

of relative GDP *given* that it is in a certain state in the starting period.

As in model specifications used in previous studies, the distribution in time $t + \tau$ depends only on $t$ and not on the distribution prior to $t$. This assumption is made because a Markov chain of higher order results in a higher dimensional state space which is computationally much more difficult to handle.

It was mentioned earlier that one advantage of the continuous kernel approach used in this paper is to avoid an arbitrary discretization of the state space. This feature, however, comes at cost: The researcher needs a lot of observations in order to get reliable estimates of the distributional dynamics.

To illustrate this point, recall that the continuous transition probability kernel $g_\tau(z|x)$ is a conditional density. In a first step to estimate the kernel, one has to estimate the joint density of $z$ and $x$. Then, the marginal density of $x$ is computed by integrating over $z$. The ratio of the joint density to the marginal density provides the estimate of $g_\tau(z|x)$. Since the density $g_\tau(z|x)$ has to be evaluated at two dimensions (i.e. at the beginning and end of the transition period), the precision of the estimation decreases dramatically if the sample size is hold constant. Effectively, this bivariate density is estimated as precisely as an univariate density only if the number of observations is squared.

If there are only a few observed transitions, then a small sample bias—which generally applies to all kernel density estimates—becomes more and more pronounced. In our nonparametric model, a small sample bias manifests itself as a bias towards a normal distribution. These considerations illustrate that the researcher needs a large number of observed transitions in order to detect non-normal distributional patterns in the kernel such as bi- or multimodality.

An efficient estimation using the largest available sample size is therefore based on annual transitions instead of transitions of multiple frequency (e.g. ten-year transitions). Quah strongly recommends this procedure because taking transition steps with long time intervals instead of annual frequencies is likely to be 'correspondingly noisy, with even fewer observations informing the estimate' (Quah 2001, p. 308). In our application, the pooled sample of one-year transitions consists of 2710 observations (271 labor market regions times 10 observed transitions), which should be sufficient for the nonparametric approach.

Distributional dynamics for longer time horizons than one year can then be illustrated by multiplying the estimated one-year transition probability kernel by itself. For example, a ten-year transition step is obtained by multiplying the one-year transition probabilities ten times. This procedure is taken as our point of departure and afterwards we will test for the robustness of the derived

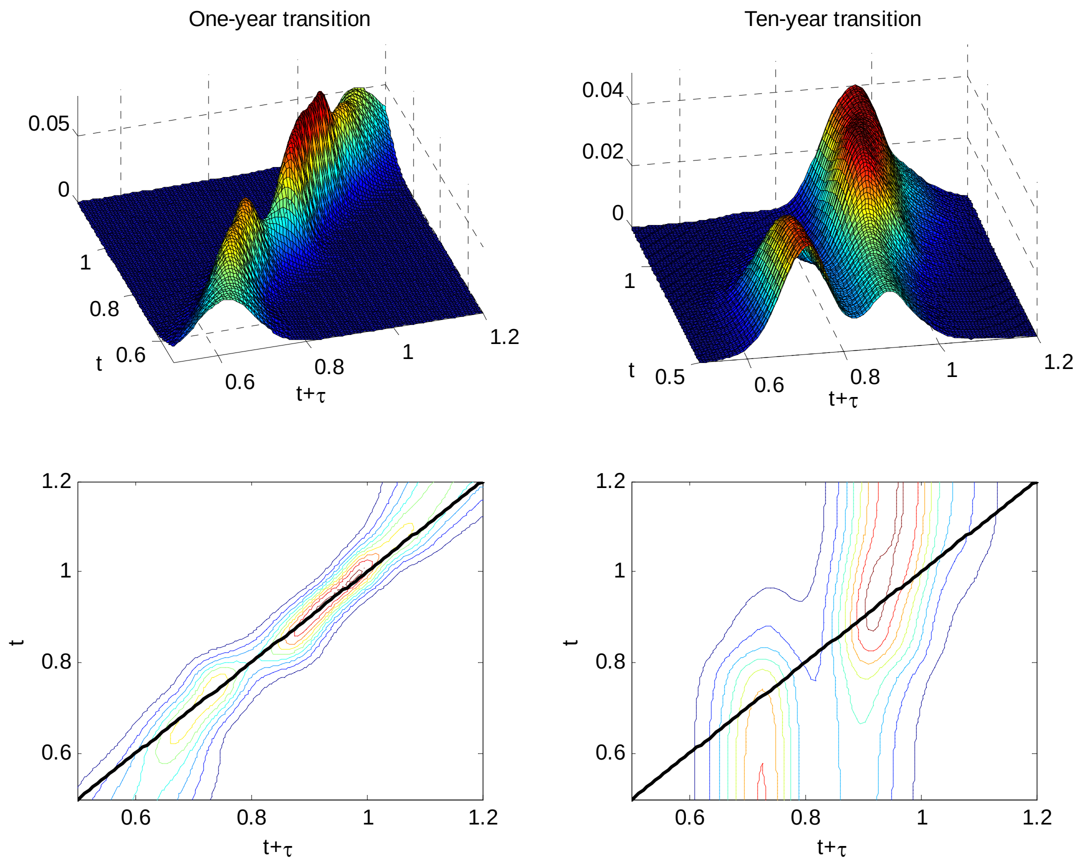


Figure 3.4: Surface and contour plots of $g_1(z|x)$ and $g_{10}(z|x)$. Left: yearly transitions between 1992 and 2002. Right: Ten-year transitions (obtained by multiplying the one-year transition probabilities ten times).

results.

As for the univariate estimations discussed in the last section, adaptive kernel techniques are employed to estimate the transition probability kernel $g_1(z|x)$ (for technical details we refer to Appendix B.2). The varying bandwidth in the adaptive procedure has the desirable effect of eliminating spurious noise at the left and right end of the joint distribution.

The estimation results are summarized in Figure 3.4. While the left figures show the mobility patterns of one-year transitions, the right figures illustrate ten-year transitions, which are obtained by multiplying the one-year transitions ten times. For both transition intervals, the upper panels display three-dimensional plots of the transition probability kernels $g_\tau(z|x)$. In these graphs, the vertical axis measures the density for each pair of points in the state space. The lines that run parallel to the $t+\tau$ axis show the probability of transiting from the corresponding point at the $t$ axis to any other point one year and ten years ahead, respectively.

The dynamics of the regional GDP distribution can be seen more clearly from contour plots of the surface of the bi-dimensional densities, as displayed in the lower panels of Figure 3.4. The thin lines in the figures connect points at the same density on the three-dimensional graphs.

To interpret the figures, recall that one can recover the probability density function associated with any point in the $t$ axis by slicing across the figure from this specific point, parallel to the $t + \tau$ axis. This projection is similar to one single row of a Markov transition matrix in which all entries sum up to one (Andrade et al., 2004). If all probability mass were concentrated around the 45°-diagonal there would be complete persistence (no mobility) in the distribution because different parts of the distribution remain where they begin. By contrast, convergence manifests itself in the kernel if most probability mass were concentrated parallel to the $t$ axis (at a value of 1 for relative GDP at the end of the transition period ($t + \tau$ axis)).

From the left column of Figure 3.4 it can be seen that the dominant feature of one-year transitions is persistence because most of the mass of the kernel is concentrated around the main diagonal. This pattern reflects that large movements in the GDP distributions are not expected year-after-year. However, a graphical examination suggests that even one-year transitions display a certain degree of mobility. For initially unproductive regions there is a shift of the probability mass towards higher relative GDP levels. Just the other way round, regions with extremely high levels of GDP per worker in the starting period tend to have decreasing GDP per worker.

This pattern already visible for one-year transitions becomes more evident from the right column of Figure 3.4, in which ten-year transitions are illustrated. Most of the mass of the conditional distribution lies below the 45° line for values of relative GDP less than 1 in the starting period and above the line for values greater than 1. This means that regions with GDP per worker below the German average in the starting period tend to have increasing relative GDP over a 10-year horizon. Similarly, regions with GDP per worker above the average tend to have decreasing relative GDP. These intra-distributional mobility patterns are consistent with a tendency towards convergence and confirm the results of the previous univariate density analysis.

However, besides revealing a tendency towards convergence, another distinct pattern of the ten-year transition probability kernel is an apparent vanishing of the middle class. The shape of the transition probability kernel for 10-year transitions indicates that the distribution's law of motion is not compatible with convergence towards a *single* point mass (e.g. towards national average GDP per worker). Rather, the density shape indicates that labor market regions congregate at two basins of attractions: One cluster of regions is characterized by a low level of relative productivity and another probability peak is at GDP per worker levels close to the national average.

So far we have examined the local maxima in the conditional density only by eye. This gives only a rough impression of the long-term outcome of the distributional dynamics. In order to perform a more formal analysis of the long-run distribution of regional GDP we calculate the density of the ergodic distribution implied by the estimated transition probabilities.

### 3.4.3 Long-term analysis

If it is assumed that the law of motion of the distribution which is estimated from past data is stable over time the transition probabilities $g_\tau(z|x)$ can be projected further into the future to calculate the implied ergodic or long-run density function of relative GDP (so long as it exists). The long-run density, $f_\infty(z)$, is the solution to

$$f_\infty(z) = \int_0^\infty g_\tau(z|x) f_\infty(x) dx. \tag{3.2}$$

If there is long-run convergence towards average GDP per worker, the ergodic density should be unimodal with a mean close to one. By contrast, multiple peaks in the ergodic distribution are usually interpreted as evidence of 'convergence clubs' in the long run. Then, some regions catch up with one another but only within particular subgroups (Baumol, 1986).

We suggest two methods to solve for the ergodic density, $f_\infty(z) = f_\infty(x)$. An intuitive approach is to multiply the transition probability kernel $g_\tau(z|x)$ many times by itself until the density has converged, which means, until all rows of the transition probability kernel are equal. Using this iterative procedure, observed transition probabilities are projected further into the future.

The second way is related to an eigenvector and eigenvalue problem. Johnson (2005) has shown that the stationary distribution can be represented as an eigenvector of $g_\tau(z|x)$ corresponding to the eigenvector one.[10] Both approaches

[10] For an elaborate presentation of this idea, see the webappendix of Johnson (2005), downloadable from `http://irving.vassar.edu/faculty/pj/pj.htm`. The author explains how to solve numerically for $f_\infty(z) = \int_a^b g_\tau(z|x) f_\infty(x) dx$, where $a$ and $b$ define the

yield the same result.

An important aspect of the limiting distribution is that it is, by construction, independent of the starting positions of particular regions (Quah, 2001). It shows the likelihood of becoming a less productive, mildly productive, or very productive region independent of the starting value of relative GDP per worker. Therefore, one has to keep in mind that the ergodic density does not allow inference which labor market regions form the different clusters (if there are any). This issue is addressed afterwards by estimating separate laws of motion of the West and East German economies, respectively.

Moreover, the notion of the ergodic density assumes that the observed law of motion of the distribution is stable over time. This means that one can interpret the long-run density only as showing the likely outcome given that the realized transitions characterize future developments. Using the terminology of the distribution dynamics approach, the ergodic density should be interpreted as the likely long-term outcome given that the observed distributional dynamics (which may be influenced by various factors) remain unchanged.

The ergodic density implied by $g_1(z|x)$ (yearly transitions between 1992 and 2002, see Figure 3.4) is displayed as the bold line in Figure 3.5. The shape of the ergodic density function provides evidence for a tendency of the cross-regional GDP distribution to converge to a long-run distribution having two clusters, an outcome which can be called polarization (Quah, 1997). This means that the calculated ergodic density lacks an optimistic view of long-run convergence towards a unimodal GDP distribution. The left mode in the density is at a relative GDP per worker of only 73% of the national average. Becoming a region with 92% of average GDP per worker is associated with the highest likelihood. This result of long-term polarization is well in line with the graphical examination of the transition probability kernel presented in the last section.

It is instructive to compare the ergodic outcome with today's (2002) point-in-time distribution. This distribution is displayed as the thin line in Figure 3.5 (evaluated at the same equi-spaced grid points). While actual densities at a given point in time may reflect a (historical) disequilibrium due to structural shocks in the past, the ergodic density shows a future equilibrium in the absence

interval where the density is evaluated. In the numerical implementation, the stochastic transition probability kernel $g_\tau(z|x)$ is estimated as a $p \times p$ matrix $Q$, where $p$ is the number of grid points at which the conditional density is evaluated. If the largest eigenvalue of this matrix is unity then the Markov process is ergodic. The left eigenvector $\phi$ corresponding to this eigenvalue has the property $\phi = Q\phi$ and $\phi$ is the implied ergodic density.

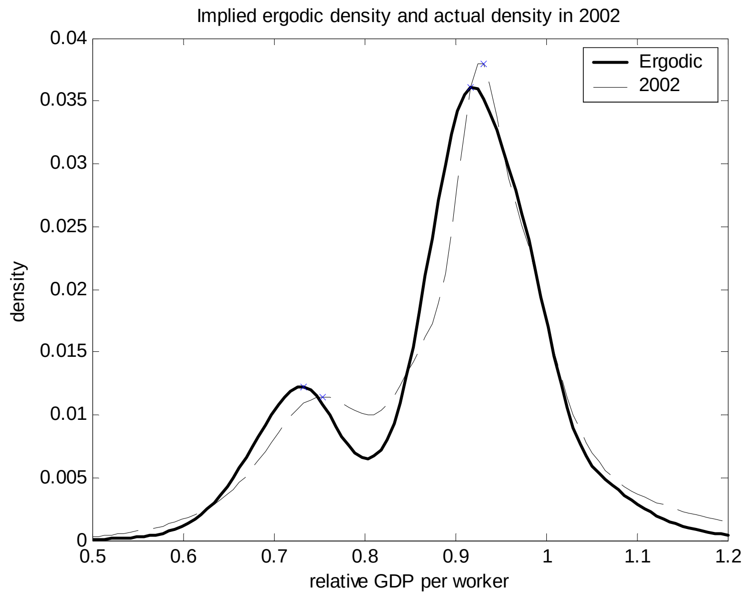


Figure 3.5: Bold line: Ergodic density of relative GDP per worker, calculated on the basis of $g_1(z|x)$ (yearly transitions between 1992-2002). Thin line: Actual density of relative GDP per worker in 2002.

of structural changes. A comparison of both densities gives an idea to what extent the actual density already resembles the external shape of the long-term outcome.

For relative GDP greater than 0.92 times the German average (the right peak) the two densities look very similar. Hence, in this part of the distribution the shape of the cross-sectional distribution in 2002 already mimics the long-run equilibrium. The most striking difference to the actual distribution in 2002 is that the long-run distribution shows an even more pronounced clustering of regions with below average GDP per worker. In other words, multimodality is less pronounced in the actual point-in-time distribution of the year 2002.

The twin-peaked shape of the ergodic density shows the advantage of the nonparametric approach used in this paper. A traditional analysis of $\sigma$-convergence typically measures the dispersion of the cross-sectional distribution by the evolution of the standard deviation of relative GDP over time. Such an analysis is problematic if distributions are not unimodal as in our application. Similarly, a traditional analysis of $\beta$-convergence does not take higher moments of the GDP distribution into account, which have to be estimated for proper inference in our setting.

The central result of our long-term analysis is that the long-run distribution of relative GDP per worker in reunified Germany is characterized by polariza-

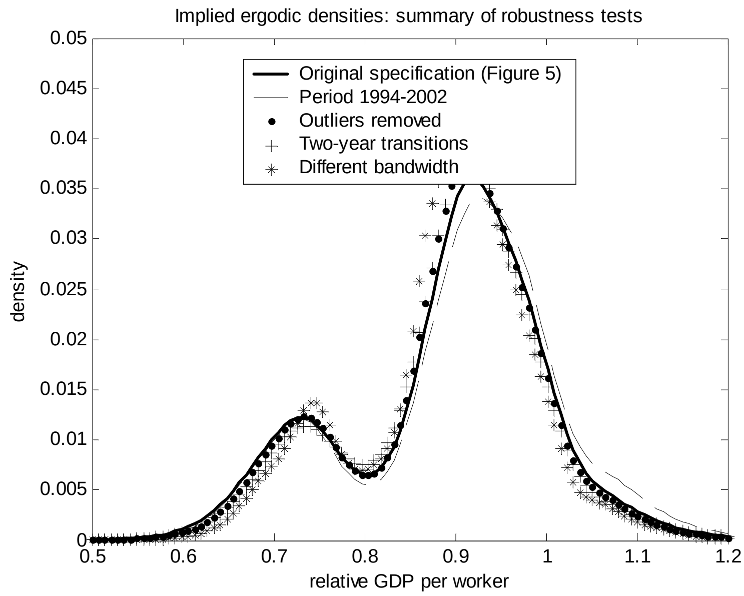


Figure 3.6: Summary of various robustness tests. 'Outliers removed': regions with the 10 highest and 10 lowest values of relative GDP per worker in 1992 are excluded in all years. 'Different bandwidth': Sheather and Jones (1991) *plug-in* bandwidth criterion.

tion if the past distributional dynamics continue operating unchanged in the future. In the next sub-section we present extensive robustness tests of this strong result and we address the question whether the peaks reflect a clustering of West and East German regions, respectively.

### 3.4.4 Robustness tests

It is well-known that the catching-up process of East German regions slowed down considerably in the second half of the last decade (see Eckey, 2001 and Barell and te Velde, 2000 for a detailed discussion). For instance, Kosfeld and Lauridsen (2004) attribute the lack of significant conditional convergence obtained in their cross-sectional study referring to the year 2000 to the apparent convergence slowdown. Therefore, one might argue that a long-term forecast based on the period 1992-2002 is even likely to overstate the extent of convergence because the comparatively fast initial catching-up process of East German regions in the first years after German reunification is unlikely to be representative for future periods. Therefore, we exclude the first years after German reunification from the analysis, which were turbulent years after the political turn, and estimate the long-run distribution using data for the more stable period 1994-2002 only. As we would expect, our previous result of polarization is confirmed under this specification (see Figure 3.6 for a summary of the alternative estimation results discussed in this sub-section).

Moreover, we check if the estimated distributional dynamics which underlie the long-run density are heavily influenced by outlying data points. As simple tests, we exclude the regions with the 5 (10) highest and 5 (10) lowest values of relative GDP per worker in 1992 from the analysis (in all years). Both, the estimated long-run densities, and the actual point-in-time distributions (not reported) of these sub-samples do not change significantly and the peaks of the ergodic densities are similar as for the whole set of regions (see Figure 3.6).

Another sensitive point in our analysis might be the assumed frequency of transitions. For this reason, we test if the twin-peaked outcome of the long-run density is heavily dependent on the use of annual transitions. Again, it turns out that the results are robust. We tried using two-year and three-year transitions. In both cases, the ergodic density shows a similar pattern of polarization (see Figure 3.6).

Finally, we test if our results are exceedingly sensitive to the employed method to select the bandwidth of the pilot density estimate in the adaptive procedure. It has been shown that the *plug-in* procedure suggested by Sheather and Jones (1991) performs consistently well over a wide range of density shapes. As an alternative to Silverman's (1986) adaptive rule of thumb we select the optimal bandwidth of the pilot density according to this criterion. From Figure 3.6 it can be seen that our results are not very sensitive to the bandwidth selection method.

We also smoothed the data by using a logarithmic transformation of the relative GDP per worker variable. The logarithmic transformation, which is frequently applied in related studies, affects the shape of the density distribution of the original data. The results obtained with the log-transformed data are very similar to our preferred specification reported above. The left peak corresponds to $\exp(-0.3131) = 0.7312$ and the right peak to $\exp(-0.0707) = 0.9317$ times the national average GDP per worker (the figure is available from the author on request).

Thus far, we have assumed that all German regions evolve according to a common law of motion. One might argue, however, that the transitional dynamics of West and East German regions are fundamentally different. Similarly, the two clusters in the ergodic density may reflect a long-term difference between East and West German regions, respectively.

As mentioned above, the bimodal ergodic density may not be interpreted as showing long-run clusters of East and West German regions if a common law of motion is assumed. This interpretation is not correct because the stationary distribution is by construction independent of the starting positions of particular regions. In order to infer whether the two clusters in fact reflect long-term East-West disparities we estimate separate laws of motion of the West and East German GDP distributions and compare the implied ergodic densities.[11]

Figure 3.7 (upper panel) provides strong evidence that the bimodal outcome of the long-run GDP per worker distribution of all German regions indeed reflects long-term disparities between West and East German regions. Both ergodic densities are unimodal. The peak of the West German distribution is at 91% of the German average while it is at 74% for East German regions. These peaks are very similar to the peaks obtained in the estimations in which a common law of motion was assumed (0.73 and 0.92, see Figure 3.5).

The separate analysis shows that West and East German regions converge to different levels of relative GDP per worker if the past laws of motion of both distributions continue operating unchanged in the future. It provides discouraging evidence that East German regions will stay considerably less productive than West German ones even in the long run, a finding which is of particular importance against the background of a decade of substantial regional policy expenditures.

A natural second step in the separate analysis is to formulate regional GDP per worker relative to the West and East German (labor force weighted) average GDP per worker, respectively, instead of relative to the *national* average GDP per worker. From the lower panel of Figure 3.7 it can be seen that East German regions form a more homogenous group than West German ones. For an East German region, the likelihood is highest to become a region with the average East German GDP per worker. Or to put it differently, most East German regions will end up with the same (comparatively low) level of GDP per worker.

[11] At first glance, another straightforward way to account for heterogeneity among regions would be to introduce fixed effects in the estimations. We believe, however, that there are both, economic as well as econometric reasons not to include fixed effects in our application. From an economic point of view it is not clear why the analysis should allow for the possibility that some (e.g. East German) regions possibly converge to significantly lower levels of relative GDP than other regions in Germany, in particular if a long-term perspective is chosen. Rather, differences in per capita output should only be transitory if absolute convergence holds. From an econometric point of view, the inclusion of fixed effects (i.e. using within-transformed data) causes similar problems as in parametric dynamic panel data models with a lagged dependent variable, i.e. some kind of Nickel (1981) bias. It is beyond the scope of this paper to extend the distribution dynamics framework to allow for fixed effects, a modification which seems a promising task for future research. To the best of our knowledge, there is no study at all which allows for unobserved heterogeneity across regions within the distribution dynamics framework.

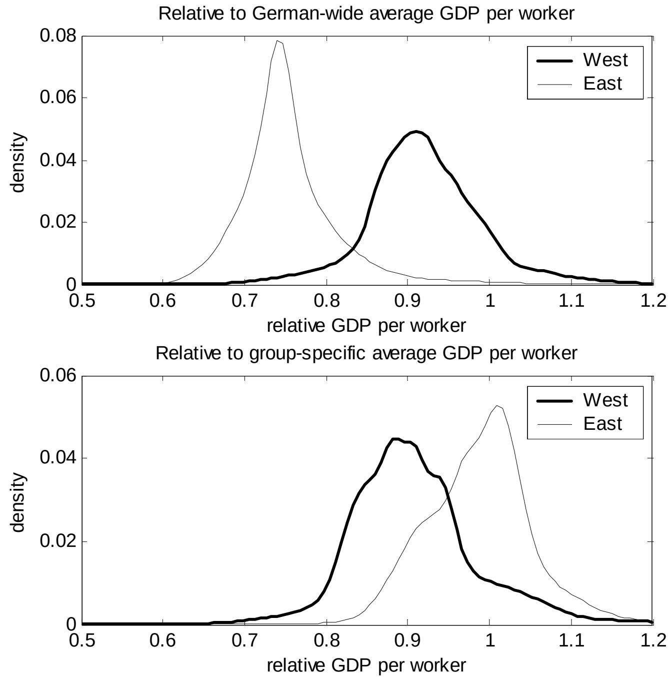


Figure 3.7: Separate analysis of the West and East German economies. Top: Implied ergodic densities of West and East German GDP per worker relative to the German-wide average GDP per worker. Bottom: Implied ergodic densities of West and East German GDP per worker relative to the West and East German average GDP per worker, respectively.

By contrast, there is more variation in the long-run distribution of West German regional GDP per worker. This ergodic density has longer tails than the one for East German regions which implies that in the long run there are also some comparatively unproductive as well as very productive regions in the Western part of Germany. These findings are well compatible with the map of German labor market regions presented in Figure 3.1. The map illustrates that in 2002, there are very productive, mildly productive, as well as comparatively unproductive regions in the Western part of Germany, while there are less disparities within the new federal states.

## 3.5 Conclusion

This paper has provided evidence for a tendency towards convergence across labor market regions in reunified Germany during 1992 to 2002. Very unproductive regions in 1992 tend to have increasing GDP per worker while extremely productive regions tend to have decreasing GDP per worker. Convergence is driven mainly by the catching-up process of East German regions in relative terms. However, despite the trend towards convergence, substantial regional disparities persist. According to our long-turn analysis, German regions are unlikely to converge towards equality in terms of GDP per worker. Rather, the long-run estimates suggest that there will be pronounced disparities also in the future. These disparities reflect long-term differences between West and East German regions as a separate analysis revealed. One should keep in mind, however, that an analysis for reunified Germany suffers from the comparatively short sample period available.

The separate analysis revealed that the distributional dynamics of West and East German regions differ. Therefore, we have to critically ask ourselves if our specification using pooled data is a reliable analysis of the German economy as a whole.

Strictly speaking, the specification using pooled data is not appropriate when East and West German regions evolve according to separate laws of motion. Then, the separate analysis would be more appropriate. In the extreme case, the process for the pooled data would not be ergodic if the two laws of motion were indeed completely separated. The concept of an ergodic density for the pooled data is therefore only meaningful if we assume that there is a certain (possibly very low) probability that East German regions may exchange their position with West German ones in the long run.

Our empirical finding of pronounced polarization in the ergodic density for the pooled data stands in stark contrast to the optimistic expectation of absolute convergence which implies that ultimately there will be convergence towards a single point mass in the (unimodal) GDP distribution. However, as emphasized by Durlauf, Johnson, and Temple (2005), there has been relatively little formal effort to explore the implications of findings such as twin-peaks for the empirical salience of alternative growth theories.

Specifically, the univariate and descriptive approach taken in this paper does not allow us to distinguish between neoclassical conditional convergence and club convergence. As Quah (1997) and others have shown, it is possible to extend the distribution dynamics approach to allow for conditioning variables. In particular, one would like to conduct a conditional analysis to the residuals from a human capital augmented Solow model and see whether the results of the conditional analysis of the distribution dynamics of the residuals mimic that of the unconditional analysis. This way, we could link the finding of polarization to the literature on nonlinearities and $\beta$-convergence (see Durlauf and Johnson, 1995 and Liu and Stengos, 1999).[12] Such multivariate approach seems the natural extension of our separate analysis of the East and West German economies.

However, time-series data on investment rates as measures of regional savings are not available at the disaggregation level required (see the discussion in Kosfeld, Eckey, and Dreger, 2002).[13] Investment in human capital is even more difficult to measure. Kosfeld, Eckey, and Dreger (2002) use a comprehensive human capital indicator which is available only for most recent years. An imperfect proxy for the human capital variable would be to use data on qualifications which are available for the subset of employees bounded to the social security system, but only since 1996 (apart from Brandenburg). These considerations illustrate that a conditioning analysis involves many new problems and challenges. Therefore, we leave the analysis of conditional convergence to further research.

[12] We would like to thank an anonymous referee for suggesting this link.

[13] Kosfeld, Eckey, and Dreger (2002) suggest to use data on newly established businesses but these data are only available for 1998 onwards.

# Part II

# Risk Sharing in Germany and the US

# Chapter 4

# Interregional Risk Sharing and Fiscal Redistribution in Reunified Germany

## 4.1 Introduction

At the heart of interregional risk sharing stand the fundamental differences between regional Gross Domestic Product (GDP), income, disposable income, and consumption. While GDP corresponds to a region's production, income explicitly includes net factor payments from other regions. By holding claims to output in other regions, individuals can smooth away idiosyncratic shocks to income caused by variations in their home region's production. Following Asdrubali, Sørensen, and Yosha (1996) (henceforth ASY) such insurance is referred to as 'income smoothing' or 'capital market smoothing'. As discussed by ASY (1996) and von Hagen (2000), in a world with imperfect capital markets, further smoothing of incomes can be achieved by the fiscal transfer system, which renders disposable income different from income. This channel of risk sharing is referred to as 'federal government smoothing'. In the extreme case of full risk sharing after capital market and federal government smoothing, idiosyncratic shocks to production do not affect disposable income at all. The desirable effect of this stabilization is that regions can achieve a smooth stream of intertemporal consumption.[1]

In most economies, fiscal transfers are not primarily intended to provide

[1] A region can further smooth its consumption by borrowing and lending on the credit market. Since consumption data are not available at the disaggregated regional level used in this paper, such *ex post* channel of 'consumption smoothing' or 'credit market smoothing' (see ASY, 1996 and Becker and Hoffmann, 2006) is not considered.

short-term risk sharing. Although fiscal transfers may turn out to have stabilizing effects, the main justification of transfers is to provide systematic and long-term redistribution from persistently rich to persistently poor regions. This is made explicit in the German constitution, which states that the main goal of the fiscal transfer system is to create and secure uniform living standards throughout Germany. In general, any persistent disparities in levels of relative economic prosperity may result from different shocks but also from permanent heterogeneity among regions.

Similar to the smoothing of output shocks by private markets, the smoothing of persistent initial disparities by fiscal redistribution can also be interpreted as a kind of insurance. Rather than providing insurance against shocks, this kind of risk sharing refers to an insurance against unfavorable initial conditions. It is an insurance in a Rawlsian sense, an insurance taken behind a veil of ignorance. Behind a veil of ignorance, individuals could be born in a rich as well as poor region. In the absence of sizeable regional migration, the risk of being born in a poor region can be insured against by redistribution of income by public institutions. The market, by contrast, is not expected to provide sufficient insurance against unfavorable initial conditions.

This implies that one has to distinguish between two kinds of risk sharing: Firstly, private markets and the public sector provide insurance against idiosyncratic *shocks* to regional output. Secondly, the public sector aims at reducing *level* disparities between regions which may result from permanent heterogeneity rather than from short-term shocks.

This paper provides new empirical evidence on both kinds of risk sharing in reunified Germany. One novelty of our study is that it introduces new empirical techniques into the risk sharing literature which rely on nonparametric density estimation. The short term and stabilizing effect of interregional risk sharing is analyzed by conditioning the densities of first-differenced income and disposable income on shocks to regional output. This conditioning allows one to assess if shocks to production are transmitted to shocks to income and disposable income. An advantage of the proposed methodology is that one can address the question of whether the relationship between the different risk sharing channels and idiosyncratic output shocks is more complex than captured by a linear regression model as proposed by ASY (1996). For example, a nonparametric approach may turn out to be useful if high risks are harder to insure than moderate risks.

In order to analyze if redistribution of the public sector contributes to a reduction of level disparities between regions, we adopt a continuous state space method to estimate the transition dynamics and calculate the implied long-run distributions of regional output, income, and disposable income. By comparing the shapes of the long-run distributions we can assess the extent of smoothing of disparities between regions achieved by private factor income flows and public interregional transfers.

The techniques employed are borrowed from the growth econometrics literature and were first introduced by Danny Quah in a number of seminal papers to analyze convergence between countries and regions (Quah, 1996a, b, c, 1997, 2001). This so called 'distribution dynamics' approach facilitates an analysis of evolving distributions which extends panel data and time-series methods and is especially useful in uncovering empirical phenomena like clumping, stratification, and polarization. As already pointed out by Quah himself (Quah 1996c, p. 117), risk sharing is one example where these phenomena are relevant. Surprisingly, the techniques from the growth econometrics literature have not been transferred yet to a risk sharing framework. Our study is the first assigning Quah's ideas to the risk sharing literature by explicitly distinguishing between the distribution dynamics of output, income, and disposable income.

While previous studies for (West) Germany have examined regional risk sharing at the level of the West German federal states (Hepp and von Hagen, 2000, Kellermann, 2001, Buettner, 2002), our study provides a regionally disaggregated analysis at the level of 271 functionally defined labor market regions. For reunified Germany, ours is the first study analyzing interregional risk sharing, most likely because appropriate data have only recently become available. The case for reunified Germany is particularly interesting because there are substantial interregional transfers aimed at reducing regional disparities, especially between the Eastern and Western part of the country. These transfers potentially provide insurance of idiosyncratic regional risk.[2]

Before we proceed to present the data and the econometric model, we provide a preview of our results. The results of the short-term risk sharing analysis are surprisingly clear-cut: Shocks to regional output are found to be almost uncorrelated to changes in regional income, a finding which provides strong evidence of almost complete risk sharing after income smoothing. The fact that regional income does not co-move with output implies that there is no scope for further smoothing of income shocks by the federal government. Indeed,

[2]In Germany, there is an explicit, formula-based arrangement for tax revenue sharing and transfers among German federal states which is defined by the German constitution. Moreover, there are separate arrangements for fiscal equalization at the municipal level in all federal states (Hepp and von Hagen, 2000).

the estimation results show that fiscal transfers, which are responsible for the wedge between income and disposable income, provide no additional insurance of idiosyncratic shocks.

Concerning the long-term redistributive properties of fiscal transfers we find that the variance reduction achieved by the fiscal transfer system is substantial. In the long run, the probability that German regions deviate from the average level of disposable income per capita is comparatively low. Since redistribution by the public sector is necessary to achieve a uni-modal distribution of regional incomes, we conclude that the fiscal transfer system reduces disparities between regions significantly. However, this redistributive policy has no short-term stabilizing effects as a by-product.

This paper is structured as follows: The data are introduced in Section 2. Section 3 focuses on the short-term stabilizing effects of interregional risk sharing. The distribution dynamics analysis of long-term disparities between regions is presented in Section 4. A brief discussion of our empirical approach is presented in Section 5. The last section presents our conclusions.

## 4.2 Data

In order to gain an understanding of regional risk sharing it is necessary to measure the regional economies carefully. Recently, detailed data for reunified Germany have become available, which facilitate a regionally disaggregated analysis at the level of 439 counties. The institution for measuring the counties' economic activity is the National Accounts of the Federal States compiled by the Statistical State Office Baden-Wuerttemberg. Our analysis of interregional risk sharing takes data on GDP, (primary) income, and disposable income into account.[3]

Gross Domestic Product (GDP) is measured in market prices and quantifies the amount of economic production of a particular region. In contrast to Gross National Product (GNP), GDP *ex*cludes interregional income transfers and hence attributes to a region the products generated within it, rather than the incomes received in it.

The income figure used in this study is the so-called primary income of private households.[4] It consists of the received compensation of employees, the

[3] All data can be downloaded from:
`http://www.statistik-portal.de/Statistik-Portal/publ.asp.`

[4] GNP data for German counties are not available. Moreover, there are no income data for other sectors.

incomes of the self-employed, and property income, e.g. interest on wealth. In contrast to GDP, primary income *in*cludes net factor payments (interregional income transfers) from other regions. A priori, the difference between regional GDP and income can be expected to be substantial because regions within a country are highly integrated.

Disposable income is defined as the amount of households' total income left after taxes, plus any transfer payments and grants received from the federal government. We denote the overall balance of levied taxes (e.g. income tax), contributions (e.g. social insurance contributions) and received transfers (e.g. pensions, unemployment benefits, social welfare) as net fiscal transfer. Disposable income is obtained from primary income by substracting the net fiscal transfer.[5] This income figure determines how much private households can consume and save and it is often seen as an indicator of the standard of living in a region.[6]

Since regions differ in size, aggregate measures of output, income, and disposable income need to be normalized by an appropriate reference variable. Usually, total population or total employment are used as a reference.

For income and disposable income, total population is the appropriate reference because income is measured at the place of residence instead of at the workplace. In contrast, total employment appears to be the more appropriate reference for data on production, because both, GDP and the number of employed people refer to the workplace.[7]

This difference between data referring to the place of residence and to the workplace might cause problems in our analysis of interregional risk sharing because regions within a country are integrated by commuter flows. If commuting linkages between regions are not accounted for in the employed data,

[5] Previous studies on interregional risk sharing and fiscal federalism distinguish between the smoothing effects of different levels of the fiscal equalization system such as taxes, transfers, and grants (Sørensen and Yosha, 1999, Buettner, 2002). Unfortunately, it is not possible to analyze the composition of federal government smoothing at the fine level of regional aggregation used in this paper because these data are not available. Nevertheless, one still can compare incomes before and after redistribution of the fiscal sector, i.e. income versus disposable income.

[6] Official statistics does not report data on consumption at the county level. Therefore, working with disposable income data is the best we can do. It is well-known from other countries that even if consumption data are available they are frequently measured imprecisely and noisily (ASY, 1996). Moreover, as argued by Athanasoulis and van Wincoop (2001), over longer horizons one can expect consumption growth to closely follow the growth rate of income after risk sharing. Unfortunately, official statistics does not provide regional price indices at the county level.

[7] Population or employment data disaggregated for age groups are not available for the whole time period under study.

a properly specified risk sharing model needs to isolate the smoothing effects of commuting and suburbanization from other channels such as capital market and federal government smoothing. A further problem associated with the use of disaggregated county data is that the borders of German counties are determined by political and historical rather than economic reasons.

For these reasons we aggregate counties to local labor market regions which are the target areas for the most important regional policy program in Germany, the so called GRW (German 'Gemeinschaftsaufgabe Verbesserung der regionalen Wirtschaftsstruktur'). We use data for 439 German counties to define 271 labor market regions, so that center and hinterland of labor markets are adequately integrated on the basis of commuter flows. Due to this aggregation the employed data on GDP, income, and disposable income already account for the most important commuting linkages between regions and we can express all variables in terms of per capita as is usually done in the risk sharing literature.[8]

To account for the potential role of German-wide shocks (time-specific effects) that may create uninsurable output variability, we have formulated the data for each labor market region relative to the German-wide aggregate. This normalization also accounts for common changes in inflation. The key variables in our study are the region's logarithmic or percentage deviations from the national average per capita values of production, income, and disposable income. To save on notation, we denote relative variables with lower-case letters, so relative output per capita is $gdp = \log \frac{GDP}{GDP^*}$, relative income is $inc = \log \frac{INC}{INC^*}$, and relative disposable income is $dinc = \log \frac{DINC}{DINC^*}$, whereas the variables indicated with a star denote the population-weighted national average values. In the following, we use the term 'relative' as equivalent to 'idiosyncratic'.

These relative variables do not only reflect the influence of shocks but also include the permanent heterogeneity among regions. This means that the levels of $gdp$, $inc$, and $dinc$ include the fixed effect of each region. In order to measure idiosyncratic shocks, we will work with first differences of our key variables $gdp$, $inc$, and $dinc$ which by construction no longer include the fixed effects of the variables in levels. The first differences of the relative variables measure the deviation of a region's growth rate from the average growth rate in Germany as a whole.

The empirical analysis employs annual data in the period from 1995 to 2002. Data from earlier years are only available for GDP but not for primary

[8] Since all our measures—output, primary income, and disposable income—are in per capita terms we often omit 'per capita' for the sake of brevity. Population data are reported by the Federal Office for Building and Regional Planning.

and disposable income. Thus, our database consists of a balanced panel of 271 regions observed over 8 years.[9]

## 4.3 The short-term stabilizing effects of interregional risk sharing

In this section to what extent private markets and the public sector provide insurance against idiosyncratic shocks to regional output is analyzed. As summarized by Asdrubali and Kim (2004), most of the theoretical literature on risk sharing considers a world of open endowment economies with complete markets lasting infinite periods. Each economy is populated by a representative risk-averse consumer who maximizes his expected utility in the face of an exogenous stochastic output process. Standard time- and leisure-separable utility functions imply that every representative agent will insure his future income stream in any contingency. If markets are complete, agents can pool their risk and insure fully against the idiosyncratic uncertainty in their resources. Consequently, one important empirical implication of risk sharing theory is that consumption should not co-move with idiosyncratic variables, such as regional output. Rather, changes in consumption should move parallel to aggregate changes in consumption (given that preference shocks and measurement error are absent).[10]

The study of risk sharing *channels* was introduced by ASY (1996) and adds to the analysis the correlation between GDP and additional national accounts measures, such as income, disposable income, and ultimately consumption. As discussed in the last section, we can only work with data on disposable income because consumption data are not available at the disaggregated regional level used in this paper. We follow the ideas of ASY (1996) and Sørensen and Yosha (1998) and consider the following identity of per capita output, income, and disposable income:[11]:

$$gdp_i = (gdp_i - inc_i) + (inc_i - dinc_i) + (dinc_i)\,. \tag{4.1}$$

In order to obtain a simple measure of smoothing from the identity, one ma-

[9] The database only covers a rather short time period but one has to keep in mind that a richer database is simply not available for reunified Germany.

[10] For more details on risk sharing theories we refer to Cochrane (1991), Sørensen and Yosha (1998), Crucini (1999), and Crucini and Hess (2000).

[11] The decomposition suggested in the cited studies also includes consumption $cons_i$ and reads as (in logs): $gdp_i = gdp_i - inc_i + inc_i - dinc_i + dinc_i - cons_i + cons_i$.

nipulates it by taking differences and multiplying both sides by $\Delta gdp_i$ :

$$\Delta gdp_i \cdot \Delta gdp_i = (\Delta gdp_i - \Delta inc_i) \cdot \Delta gdp_i + (\Delta inc_i - \Delta dinc_i) \cdot \Delta gdp_i + (\Delta dinc_i) \cdot \Delta gdp_i. \tag{4.2}$$

Finally, one takes expectations and arrives at the following decomposition of the cross-sectional variance in $\Delta gdp$ (see ASY, 1996, Sørensen and Yosha, 1998, and Mélitz and Zumer, 1999 for further details):

$$\begin{aligned} var\{\Delta gdp_i\} &= cov\{\Delta gdp_i, \Delta gdp_i - \Delta inc_i\} \\ &\quad + cov\{\Delta gdp_i, \Delta inc_i - \Delta dinc_i\} \\ &\quad + cov\{\Delta gdp_i, \Delta dinc_i\}. \end{aligned} \tag{4.3}$$

Divide by the variance of $\Delta gdp_i$ to get

$$1 = \beta_C + \beta_G + \beta_U, \tag{4.4}$$

where $\beta_C$ is the ordinary least squares estimate of the slope in the regression of $(\Delta gdp_i - \Delta inc_i)$ on $\Delta gdp_i$. The dependent variable $(\Delta gdp_i - \Delta inc_i)$ reflects changes in capital income flows between regions (e.g. equity returns) and $\beta_C$ is interpreted as the percentage of smoothing of a GDP shock carried out by capital markets.[12]

Similarly, the coefficient $\beta_G$ is the slope in the regression of $(\Delta inc_i - \Delta dinc_i)$ on $\Delta gdp_i$. The $(\Delta inc_i - \Delta dinc_i)$ differential measures the net change in fiscal transfers and we can interpret $\beta_G$ as the percentage of smoothing of a GDP shock carried out by the federal government. Finally, $\beta_U$ is the coefficient in the regression of $\Delta dinc_i$ on $\Delta gdp_i$ and measures the amount not smoothed. In practice, the third regression needs not be estimated because the $\beta$ coefficients sum to unity.

At the practical level, the typical parametric risk sharing regressions implied by the variance decomposition method are specified as panel regressions and

[12] One has to keep in mind that the $gdp - inc$ differential also captures retained earnings. There are no data available which can be used to disentangle the effects. Athanasoulis and van Wincoop (2001) argue that retained earnings do not alter the economic interpretation of capital market risk sharing substantially because retained earnings reflect an investment that contributes to dividends in the future.

can be summarized as follows (all variables are in stacked form):

$$\begin{aligned} \Delta gdp - \Delta inc &= \beta_C \Delta gdp + u_1 \\ \Delta inc - \Delta dinc &= \beta_G \Delta gdp + u_{2,} \end{aligned} \tag{4.5}$$

whereas $\beta_C$ and $\beta_G$ measure the average degree of capital market and federal government smoothing, respectively. The $\beta$ coefficients will be weighted averages of the year-by-year cross-sectional regressions (see ASY, 1996, footnote 5). In both regressions, the right-hand side variable is the idiosyncratic shock to output and the slope parameters measure the percentage of shocks to output which are absorbed at each level of smoothing. Full risk sharing is present if $\beta_C$ and $\beta_G$ sum to unity.[13]

This paper suggests an alternative method of analyzing risk sharing which is based on nonparametric density estimation as proposed by Quah (1997) in the context of convergence studies. Our basic idea is to combine ASY's (1996) regression specification as summarized in (4.5) and Quah's (1997) distribution dynamics approach.

Quah's original approach is concerned with mapping whole distributions sequentially in time. This procedure will turn out to be especially useful in estimating the long-term redistributive effects of interregional risk sharing and is introduced in more detail in the next section. In this section, we suggest a slight modification of Quah's dynamic approach to analyze the short-term stabilizing effects of risk sharing.

By estimating the conditional densities $f(\Delta gdp - \Delta inc | \Delta gdp)$ and $f(\Delta inc - \Delta dinc | \Delta gdp)$ we can test if shocks to regional output are transmitted to shocks to income and disposable income. This means that instead of mapping the distributions of single variables (*gdp*, *inc*, and *dinc*) sequentially in time,[14] we estimate the (contemporaneous) conditional densities of variables in first differences. These densities show the likelihood of changes in private factor income flows (or net fiscal transfers, respectively) given that a region is subject to an idiosyncratic shock to its production. In a nutshell, such analysis is the nonparametric equivalent à la Quah (1997) to the parametric risk sharing regressions as displayed in (4.5). To compare the results obtained with our method to those of linear techniques we will also perform a simple regression-

[13] This can be seen more clearly by rewriting the first regression $\Delta gdp - \Delta inc = \beta_C \Delta gdp + u_1$ as $\Delta inc = (1 - \beta_C)\Delta gdp + u_1$. If $\beta_C$ equals 1, income does not co-move with output. Similarly, if full risk sharing is achieved at the federal government level, *dinc* should not co-move with *gdp*. As in previous studies, we do not impose any restrictions on the estimated coefficients.

[14] This will be done in the next section.

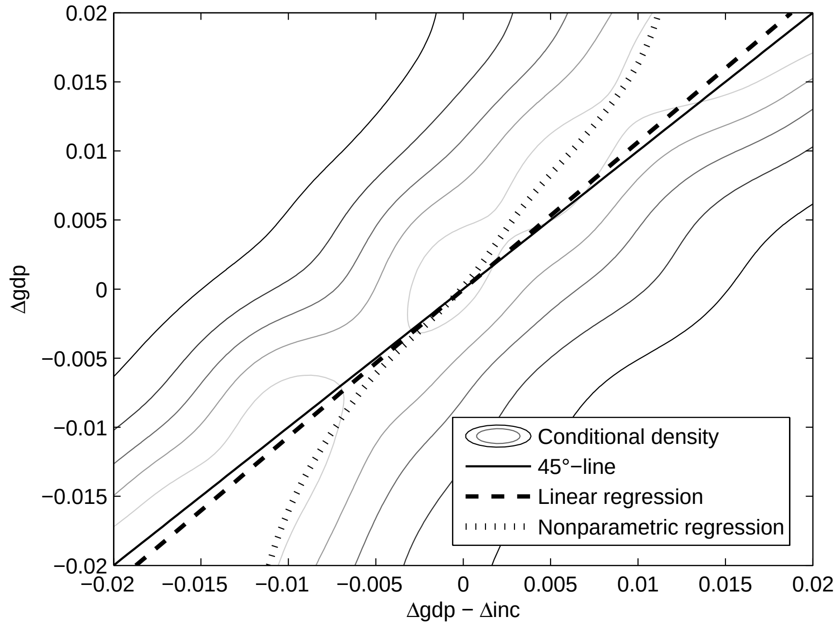


Figure 4.1: Contour plot of $f(\Delta gdp - \Delta inc|\Delta gdp)$ (capital market smoothing of idiosyncratic output shocks)

based risk sharing analysis.

The conditional densities $f(\Delta gdp - \Delta inc|\Delta gdp)$ and $f(\Delta inc - \Delta dinc|\Delta gdp)$ are estimated using adaptive kernel techniques (Silverman, 1986, Pagan and Ullah, 1999).[15] We briefly explain how to estimate the conditional densities using the density $f(\Delta gdp - \Delta inc|\Delta gdp)$ as an example. First, we have to estimate the joint density of $(\Delta gdp - \Delta inc)$ and $\Delta gdp$ using adaptive kernel techniques. Then, we compute the marginal density of $\Delta gdp$ by integrating over $(\Delta gdp - \Delta inc)$. The ratio of the joint density to the marginal density provides the estimate of $f(\Delta gdp - \Delta inc|\Delta gdp)$.

Figures 4.1 and 4.2 show the contour plots of the surface of the conditional densities $f(\Delta gdp - \Delta inc|\Delta gdp)$ and $f(\Delta inc - \Delta dinc|\Delta gdp)$ which were estimated using pooled data for all years (1897 observations). The thin lines in Figures 4.1 and 4.2 connect points at the same density on the three-dimensional

[15] Adaptive estimators with a varying rather than fixed bandwidth have the desirable effect of separating different modes of the density more clearly. The adaptive kernel estimator adapts to the sparseness of the data by varying the bandwidth inversely with the density. This means that a broader bandwidth is used for observations located in regions with low density, and vice versa. Thus, adaptive estimators are able to recover more details of the density where data concentrate because the window width decreases in those regions while it increases in areas of only low data densities. Silverman's (1986, Section 3.4.2) rule of thumb is used to determine the bandwidth of the pilot density estimate in the two-step adaptive kernel estimation. All computations are performed using MATLAB.

graph of the conditional densities (output omitted). The displayed regression lines will be explained later.

To illustrate how to interpret the figures, we can consider the conditional density $f(\Delta gdp - \Delta inc|\Delta gdp)$ as an example (Figure 4.1). If all mass of this density were concentrated only parallel to the $\Delta gdp$ axis at a value of 0 for ($\Delta gdp-$ $\Delta inc$), idiosyncratic output shocks would not be insured at all. Such density shape would indicate that given that a region has a certain output shock, there would be a high likelihood that this shock were perfectly transmitted to a change in income of similar magnitude. Risk sharing would be absent because there would be no adjustment in net factor income flows between regions ($\Delta gdp - \Delta inc$) in response to an idiosyncratic output shock $\Delta gdp$. In other words, there would be no difference between the change in relative output and the change in relative income, regardless of the size of shocks to output.

In contrast, perfect risk sharing already at the capital market level manifests itself in the kernel if most probability mass were concentrated around the 45°-diagonal. In this case, relative income would not co-move with relative output. To examine the smoothing effects of the federal government, the shape of the conditional density $f(\Delta inc - \Delta dinc|\Delta gdp)$ as displayed in Figure 4.2 is interpreted analogously.

Figure 4.1 provides strong evidence of almost complete risk sharing after capital market smoothing. Most of the mass of the conditional density is concentrated around the main diagonal which indicates that shocks to regional production have no substantial influence on changes in income. This means that shocks to output $\Delta gdp$ induce a change in factor income flows ($\Delta gdp - \Delta inc$) in the same direction and of similar magnitude. However, the shape of the density also suggests that large positive or negative output shocks are partly transmitted to changes in income.[16] This visual impression will be confirmed below.

By sharp contrast, there is almost no evidence for a smoothing effect of the federal government (Figure 4.2). Since the mass of the conditional density $f(\Delta inc - \Delta dinc|\Delta gdp)$ is concentrated parallel to the $\Delta gdp$ axis there is no evidence for an additional insurance effect of the public sector. In other words, shocks to regional output $\Delta gdp$ do not induce a change in net fiscal transfers ($\Delta inc - \Delta dinc$).

In order to test if these strong results are confirmed by a parametric regression analysis, we also estimate the risk sharing regressions (4.5). If $\beta_C$ is

[16] With (absolutely) large shocks we mean those values of $\Delta gdp$ which are close to the left or right boundary of the grid interval.

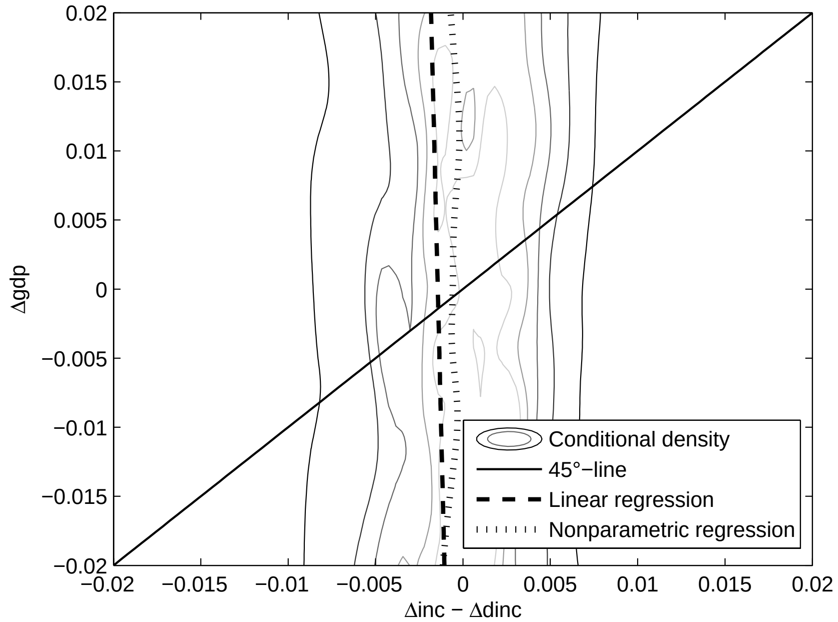


Figure 4.2: Contour plot of $f(\Delta inc - \Delta dinc|\Delta gdp)$ (federal government smoothing of idiosyncratic output shocks)

estimated close to 1 and $\beta_G$ close to zero (or insignificant), we would obtain a similar pattern of almost complete risk sharing after capital market smoothing and virtually no risk sharing after federal government smoothing.

Indeed, this is the pattern found in the data (see Table 4.1). While a simple OLS regression yields an estimate of $\beta_C = 0.937$, the estimated coefficient for $\beta_G$ is found to be negative ($-0.019$).[17] The results of this estimation indicate that only 8% of idiosyncratic output shocks are not smoothed after both channels of risk sharing. The federal government, however, is found to have a (slight) destabilizing function. Hence, the results of the parametric regression analysis are well in line with our nonparametric density analysis.

The examination of Figure 4.1 suggests that a parametric regression approach possibly hides important information which could be detected in a nonparametric regression framework. Fortunately, the estimated conditional densities $f(\Delta gdp - \Delta inc|\Delta gdp)$ and $f(\Delta inc - \Delta dinc|\Delta gdp)$ already incorporate a simple nonparametric regression. We simply have to multiply the estimated conditional densities with the grid points at which the density was evaluated.[18]

[17] Both coefficients are significantly different from zero at the 1% level. Controlling for region-specific fixed-effects in the idiosyncratic growth rates by removing region-specific means from all variables has close to no influence on the estimation results obtained with plain OLS.

[18] The same equi-spaced grid is used on both axis. A deeper nonparametric regression

Table 4.1: OLS estimates of risk sharing channels (percent)

| | 1996-2002 | |
|---|---|---|
| Capital markets ($\beta_C$) | 0.937 | (0.007) |
| Federal government ($\beta_G$) | -0.019 | (0.005) |
| Not smoothed ($\beta_U$) | 0.082[1] | |

Percentage of shocks to Gross Domestic Product absorbed at each level of smoothing. Standard errors are in parentheses. Number of observations: 1897.
[1]Calculated as $1 - \beta_C - \beta_G$

In order to facilitate a comparison of a) the nonparametric conditional density approach, b) the parametric regression approach, and c) the nonparametric regression approach, we display both regression lines in the same graph as the conditional densities.

From Figure 4.1 it can be seen that the nonparametric regression indeed reveals some nonlinearities which cannot be detected with the linear model. The shape of the nonparametric regression indicates that moderate risks are almost completely insured. However, large positive or negative shocks on the grid interval are partly transmitted to changes in income. This pattern indicates that these risks are harder to insure on the capital market than small risks.

The shape of the conditional density and the nonparametric regression line show the advantage of the nonparametric approach suggested in this paper. As argued by Danny Quah in the context of convergence studies, by focusing on the average behavior of a representative region, a linear regression model potentially suppresses important distributional patterns the researcher is interested in (see the arguments in Quah, 1996a, 1997). Our results suggest that this problem may also apply for interregional risk sharing studies. In our application, the linear regression for capital market smoothing is flatter than the nonparametric regression. Hence, the linear framework overstates the degree of risk sharing for those risks which are measured on the grid interval.

analysis (e.g. local polynomial regression or average derivative estimation) is beyond the scope of this paper. Such analysis could shed more light on the exact nature of the nonlinearities detected with our simple nonparametric regression, which is motivated by Quah's distribution dynamics approach.

For federal government smoothing (Figure 4.2), however, the nonparametric regression is not substantially different from the linear regression line.

That much is certain, the most important feature is that both the nonparametric as well as the parametric approach suggest a consistent result concerning short-term interregional risk sharing: While private markets provide almost complete insurance against shocks, the federal government does not contribute to a stabilization of regional incomes. According to the results of our estimation, fiscal transfers in reunified Germany can hardly be justified with reference to a potential stabilizing effect on regional incomes. Such insurance effect cannot be found in the data.

However, as discussed in the Introduction, fiscal transfers are not only intended for stabilization, but mainly for long-term redistribution. We argued that such redistribution can also be interpreted as a kind of risk sharing: Rather than being concerned with the smoothing of idiosyncratic shocks, the public sector can provide a smoothing of permanent heterogeneity among regions. In order to analyze if fiscal transfers achieve a long-term reduction of regional disparities by systematic redistribution of incomes, we analyze the distribution dynamics of relative output, income, and disposable income. In contrast to the short-term risk sharing analysis performed in this section, a long-term analysis of risk sharing is concerned with the levels of relative variables rather than their first differences.

## 4.4 The long-term redistributive effects of interregional risk sharing

In this section we analyze to what extent the public sector reduces long-term differences in the relative position of a region, reflecting its economic development relative to the national average. In other words, we provide evidence whether long-term differences in relative production are also reflected in long-term differences in income and disposable income. To do so, we adopt the distribution dynamics approach to economic convergence which was proposed by Quah (1997).

In a first step, we estimate a probability model of transitions which captures a distribution's law of motion. This means that we examine how a given individual of the distribution of *gdp*, *inc*, and *dinc* at time $t$ transits to another part of the distribution by the time $t + \tau$. In a second step, we follow recent developments in the growth convergence literature (Johnson, 2000, 2005) and calculate the densities of the implied ergodic distributions on the basis of the estimated distributional dynamics in a continuous framework. As explained below, a comparison of the ergodic densities of *gdp*, *inc* and *dinc* allows one to assess the degree of (level) smoothing achieved by private and fiscal institutions.

### 4.4.1 Estimating distribution dynamics and the implied ergodic density

One possibility of estimating transition probabilities is to discretize the state space and then count the observed transitions out of and into distinct discrete cells of a Markov transition probability matrix (Quah, 1993). However, Bulli (2001) has shown that an arbitrary discretization of the state space alters the probabilistic properties of the data. A better approach is to use no discretization but instead to allow the number of cells of the Markov transition probability matrix to tend to infinity (Quah, 1997). In this continuous case, the transition probability 'matrix' becomes a stochastic kernel. Such a kernel is a huge non-negative matrix whose rows sum to unity, satisfying regularity conditions to ensure that a limiting distribution exists (Quah, 2001).

To estimate the transition dynamics of *gdp*, *inc*, and *dinc* in a continuous framework, we suppose that the distribution of a variable $x$ can be described by the density function $f_t(x)$, where $x$ is variously *gdp*, *inc*, and *dinc*.[19] In general, this distribution will evolve over time so that the density prevailing at time $t+\tau$ for $\tau > 0$ is $f_{t+\tau}(x)$. Assuming that the process describing the evolution of the distribution is time-invariant and first-order Markov, the relationship between the two densities can be written as

$$f_{t+\tau}(z) = \int_0^\infty g_\tau(z|x) f_t(x) dx, \tag{4.6}$$

where $g_\tau(z|x)$ is the $\tau-$period ahead density of $z$ conditional on $x$. For example, $z$ could be relative GDP in 2002 and $x$ the same variable in 1995. The transition probabilities $g_\tau(z|x)$ encode all information about the evolution of the sequence of distributions over time and map the distribution from period $t$ to period $t+\tau$.

Similar to the last section, the stochastic kernel $g_\tau(z|x)$ is a conditional density. However, there is an important difference between the conditional densities $g_\tau(z|x)$ for *gdp*, *inc*, and *dinc* and the conditional densities $f(\Delta gdp - \Delta inc|\Delta gdp)$ and $f(\Delta inc - \Delta dinc|\Delta gdp)$. The former densities map a single

[19] This simplified presentation of Quah's (1997) methodology was proposed by Johnson (2000, 2005).

variable sequentially in time. This means that the kernel $g_\tau(z|x)$ shows the probability that a given region transits to a certain state of relative GDP (income, disposable income) given that it is in a certain state of relative GDP (income, disposable income) in the starting period.

The estimated transition probability kernel $g_\tau(z|x)$ describes the distribution's law of motion. If one assumes that this law of motion is stable over time, the transition probabilities can be projected further into the future, to calculate the implied stationary (or ergodic) distribution. While actual densities at a given point in time may reflect a (historical) disequilibrium due to structural shocks in the past, the ergodic density shows a future equilibrium in the absence of structural changes. An analysis of the long-term properties of risk sharing is therefore concerned with the ergodic rather than actual point-in-time densities.

Given an estimate for $g_\tau(z|x)$, the implied long-run density $f_\infty(z)$, given that it exists, is the solution to

$$f_\infty(z) = \int_0^\infty g_\tau(z|x) f_\infty(x) dx. \tag{4.7}$$

We suggest two methods to solve for the ergodic density, $f_\infty(z) = f_\infty(x)$. An intuitive approach is to multiply the transition probability kernel $g_\tau(z|x)$ multiple times by itself until the density has converged, which means, until all rows of the transition probability kernel are equal. Using this iterative procedure, observed transition probabilities are projected further into the future.

The second way is related to an eigenvector and eigenvalue problem. Johnson (2005) has shown that the stationary distribution can be represented as an eigenvector of $g_\tau(z|x)$ corresponding to the eigenvector one.[20] We checked that both approaches yield the same result.

Before introducing the economic interpretation of the ergodic densities of *gdp*, *inc*, and *dinc* it is important to note that the limiting distribution is, by construction, independent of initial conditions. This property becomes evident if one recalls that the ergodic density can be calculated by multiplying the

[20] For an elaborate presentation of this idea see the webappendix of Johnson (2005), downloadable from `http://irving.vassar.edu/faculty/pj/pj.htm`. The author explains how to solve numerically for $f_\infty(z) = \int_a^b g_\tau(z|x) f_\infty(x) dx$, where $a$ and $b$ define the interval where the density is evaluated. In the numerical implementation, the stochastic transition probability kernel $g_\tau(z|x)$ is estimated as a $p \times p$ matrix $Q$, where $p$ is the number of grid points at which the conditional density is evaluated. If the largest eigenvalue of this matrix is unity then the Markov chain is ergodic. The left eigenvector $\phi$ corresponding to this eigenvalue has the property $\phi = Q\phi$ and $\phi$ is the implied ergodic density.

distribution's law of motion multiple times by itself. If there are sufficient iterations the influence of the starting positions of particular regions becomes more and more negligible.

Keeping this important property in mind, one can interpret the ergodic density from the perspective of a *single* region. The underlying assumption of the ergodic density is that a single region has moved many times between the states of the Markov chain according to the unchanged law of motion $g_\tau(z|x)$. By construction, the ergodic density shows how often the region realizes the distinct states, asymptotically independent of the starting position of the particular region. This means that for a single region, the ergodic density shows the *likelihood* of certain outcomes.

For example, if the density of the ergodic distribution of one of our relative variables is uni-modal with a peak at 0 (in logs), there is a very high likelihood that a region realizes the average outcome. In other words, such pattern of the ergodic density would imply that in the long run the likelihood is highest that a region *becomes* one with an average outcome.

Besides the number of distinct peaks, one also has to examine the dispersion of the ergodic density. If the dispersion is small it is unlikely that extreme values are realized. By contrast, a large standard deviation indicates a pronounced variation.

A comparison of the implied long-run distributions of relative output, income, and disposable income allows one to assess the extent of smoothing achieved by private and public interregional transfers. One could also say that the ergodic distributions show the 'risk' of becoming a poor or rich region in terms of *gdp*, *inc*, and *dinc*. To illustrate this, consider an extreme case. If regions were not integrated by factor movements and if there were no fiscal transfer system, regions would be completely isolated and there would be no interregional risk sharing. In such a setting, differences in production would be fully mirrored in both, income as well as disposable income. Consequently, the shape of the ergodic densities of *gdp*, *inc*, and *dinc* would be equal. By contrast, if private institutions absorb differences in regional production and if there is significant redistribution of regional incomes by the public sector, the long-run distributions of output, income, and disposable income will differ.

In our methodological framework of distribution dynamics one finds evidence for a reduction of disparities achieved by risk sharing if the ergodic density of relative income has smaller dispersion than the ergodic density of relative output. Similarly, the extent of redistribution achieved by the federal government is revealed by the shape of the ergodic density of *dinc* in comparison to *inc*. The former density should have a smaller dispersion than the latter.

If there is a large cross-section of regions, the ergodic densities also have a cross-sectional interpretation. If it is assumed that the distribution of a cross-section of regions has evolved for a very long time according to the unchanged law of motion $g_\tau(z|x)$, the influence of the starting positions of different regions will have vanished. In such a setting, the ergodic density shows the shape of the distribution if past dynamics continue operating unchanged in the future.

For example, suppose that the ergodic density of the relative income variable turns out to be bi-modal; one peak corresponds to a high relative income and the other one to a low income. This pattern would imply that in the long run there are both, relatively rich as well as poor regions in the cross-section. Hence, one would find evidence for the existence of inequality in the long run which usually is referred to as 'convergence clubs'.

### 4.4.2 Estimation results

The estimated distribution dynamics of *gdp*, *inc*, and *dinc* are based on one-year transitions taking place between 1995 and 2002. This means that we pool the observed transitions 1995-1996, 1996-1997 and so on. The use of annual transitions instead of longer time intervals is strongly recommended by Quah because taking transition steps with long time intervals instead of annual frequencies is likely to be 'correspondingly noisy, with even fewer observations informing the estimate' (Quah, 2001, p. 308). The sample consists of 1897 observations (271 labor market regions multiplied by 7 observed transitions).

Based on the estimated transition probability kernels $g_\tau(z|x)$ (see equation (4.6)) we calculate the ergodic densities of regional output, income, and disposable income (see equation (4.7)).[21] Figure 4.3 displays the estimation results. All densities have been normalized so that the densities show the likelihood of a realization of *gdp*, *inc*, and *dinc* in the grid interval.

#### 4.4.2.1 GDP vs. income

Although private markets are not expected to provide substantial insurance against unfavorable initial conditions, it is nevertheless instructive to compare the long-run distributions of output (*gdp*) and income (*inc*). As the literature points out, the capital market may provide insurance, not only against tran-

[21] The transition probability kernels $g_\tau(z|x)$ are conditional densities. To estimate these densities we can use the same econometric toolkit as developed in the last section. Again, we use adaptive kernel techniques.

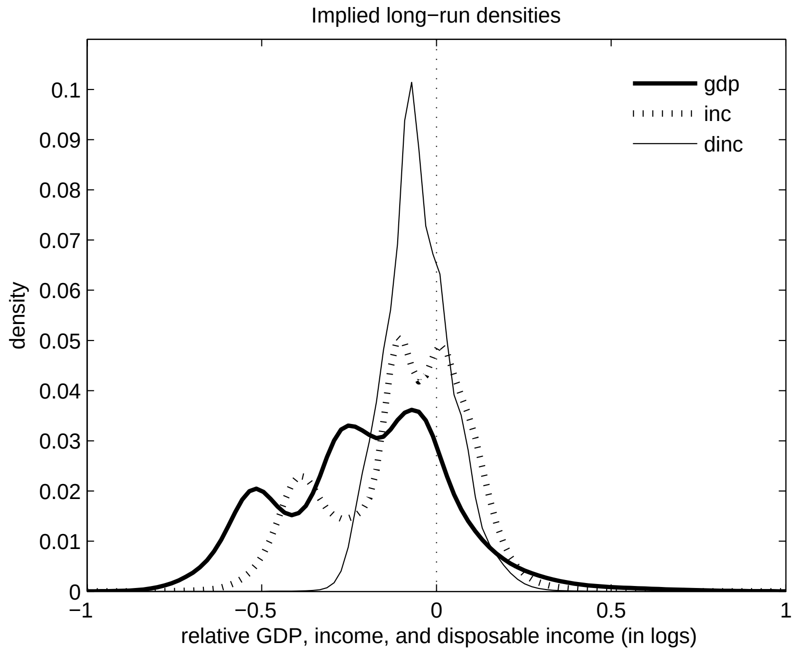


Figure 4.3: Ergodic densities of relative output, income, and disposable income, calculated on the basis of $g_1(z|x)$ for *gdp*, *inc*, and *dinc* (yearly transitions between 1995-2002)

sitory, but also against permanent shocks (Becker and Hoffmann, 2006).[22] If stochastic shocks to output and income differ, it is well possible that the long-run distribution of income is smoother than the output distribution. Moreover, convergence in income may be expected to occur faster than convergence in output, because convergence in income can be achieved by trade in financial assets. By contrast, convergence in output requires a flow of productive factors themselves.

Indeed, there is some evidence for these hypotheses. Both densities (*gdp* vs. *inc*) show a three-peaked pattern. However, the peaks of the relative GDP distribution are located at lower values than the peaks of the relative income distribution. For the relative GDP distribution, the peaks correspond to 60%, 78%, and 93% of the German average while they correspond to 67%, 89%, and 101% for the relative income distribution. This means that a single region faces a higher likelihood of realizing a low value of relative production than realizing a low value of relative income. Hence, the shapes of the ergodic densities suggest that in the long run there are fewer differences in regional income than

[22] The methodology suggested in the last section cannot distinguish between transitory and permanent shocks. Such distinction would require a cointegrated VAR framework. Due to the short time-period spanned by our database for reunified Germany, a sophisticated analysis of the persistence of shocks is not possible.

in regional output. This pattern is consistent with a certain smoothing effect of capital market linkages even if the variables are formulated in levels rather than in first differences as in the last section.

To further illustrate that the income distribution is smoother than the GDP distribution we compare the standard deviations of the two distributions. Since there are no sample observations of the ergodic density, one has to calculate the standard deviation directly from the estimated density. The standard deviation of the relative output distribution is 0.246 while it is 0.190 for the relative income distribution.

Taking a cross-sectional perspective of economic convergence, the multi-modal pattern of both *gdp* and *inc* indicates that German labor market regions will not become equal to one another in terms of output or income. Rather, there will be convergence clubs of both regional output and income if the past dynamics of the regional distributions remain unchanged. Since the market does not fully equalize regional income disparities, there can be scope for further income smoothing provided by fiscal redistribution.

#### 4.4.2.2 Income vs. disposable income

To analyze the long-term redistributive function of fiscal transfers we compare the ergodic densities of income (*inc*) and disposable income (*dinc*).

As can be seen from Figure 4.3 , the long-run distribution of disposable income is strongly uni-modal with a peak corresponding to 93% percent of the German average. This means that becoming a region with a slightly below-average disposable income is associated with the highest likelihood. Remarkably, in the long run, the probability that a region has a disposable income smaller than about 0.75 times the German average (-0.3 in logs) is effectively zero.

The shape of the ergodic density of *dinc* suggests that German regions do not deviate much from the average disposable income per capita. The figure clearly illustrates that the ergodic distribution of disposable income has considerably smaller dispersion than the income distribution. The standard deviation of the former is 0.098 while it is 0.190 for the latter. These numbers show that the variance reduction achieved by the fiscal transfer system is substantial. About half of the dispersion of the income distribution is smoothed away by the federal government.

For the cross-section of regions we find strong evidence of long-term convergence of disposable income because there are no convergence clubs apparent.[23] The persistent polarization in regional output and income is not transmitted to the long-run distribution of disposable income. This finding implies that fiscal redistribution strongly contributes to an equalization of incomes among regions in reunified Germany. To put it differently, income smoothing by federal fiscal institutions is necessary to achieve a uni-modal distribution of regional incomes.

On the side of the econometrics, the estimated shape of the densities of the long-run distributions of *gdp*, *inc*, and *dinc* show the advantage of the nonparametric approach proposed in this paper. Obviously, the distribution patterns are non-normal. A standard parametric regression analysis could not detect the long-term polarization outcome in *gdp* and *inc*. Therefore, this paper has shown that Quah's (1997) distribution dynamics approach is not only a powerful framework to analyze GDP convergence or divergence but it is also extremely useful to discriminate between the long-run outcomes of output, income, and disposable income.

## 4.5 Discussion

Besides having provided new empirical evidence on interregional risk sharing in reunified Germany, another contribution of this paper is to have introduced new empirical techniques into the risk sharing literature inspired by established techniques originally proposed in the growth econometrics literature. We think that the application of the distribution dynamics approach in a risk sharing framework is an advance in itself and it would be interesting to compare the results for Germany with other countries. In order to point out potential drawbacks and opportunities of the distribution dynamics framework to other researchers, we present a critical discussion of our analysis before we summarize our main results.

One caveat of our analysis is that we did not directly examine the effects of labor mobility on smoothing of GDP shocks. Interregional smoothing of earnings can be the result of commuting across the borders of a region (ASY, 1996) and commuters income may also make up a fraction of the smoothing effect attributed to the capital market. Therefore, it is an important task for future research to incorporate commuter flows in the risk sharing framework, an issue which has gained only minor attention in the literature so far.

[23] The term 'convergence' should not be interpreted as a dynamic catching-up process of poor regions. Rather, 'convergence' of disposable income only refers to a reduction of disparities through systematic redistribution by the public sector.

Moreover, due to the short time period available for reunified Germany, we did not examine the time-series properties of the data used. For other countries, however, longer time series are available and researchers should carefully examine the persistence the data display. The concept of distribution dynamics is only applicable if the employed *relative* variables are stationary. In other words, if the *absolute* per capita levels of regional output, income, and disposable income are integrated processes, one has to assume that there is a cointegrating relationship between regional variables and the respective national average values with cointegrating vector $(1, -1)$. Only if there is such long-run relationship between regional and aggregate variables, can one interpret the ergodic densities of *relative* variables also in terms of a cointegrating relationship, as we did in the present paper. By contrast, if the relative data series are integrated processes, an ergodic density in the sense of a long-run equilibrium simply does not exist because a non-stationary series is not ergodic.

Another important aspect is that our analysis does not account for spatial effects. Throughout the present paper the cross-sectional observations on regional output, income, and disposable income were treated as if they represent a random sample, that is, a collection of observations from independent and identically distributed random variables. In reality, however, regional data often display a high degree of spatial autocorrelation as well as various forms of spatial heterogeneity. Unfortunately, there is no study as of today which explores the implications that spatial effects can hold for the application of the continuous variant of the distribution dynamics approach used in this paper.

Of course, there are alternative estimation strategies which could be used to overcome the discussed limitations of the nonparametric distribution dynamics approach. For example, there are both panel data and time-series models that can account for spatial inter-dependence. The advantage of the approach pursued in the present paper comes about if the distribution is not single-peaked and high moments have to be estimated for proper inference. We fully agree with Rey and Dev's (2006) call that 'a fruitful avenue of future research is adopting a perspective where the outputs from the spatial econometric analysis become inputs into a higher order study in which the dynamics of both the income distribution and the level of spatial clustering are treated jointly'. The methodological issues on spatial regional income convergence examined in Rey (2001), Egger and Pfaffermayr (2006), and Rey and Dev (2006) can have relevance for the study of interregional risk sharing, especially the recent developments in the analysis of spatial $\sigma$-convergence. The cited studies may serve as a starting point to develop a unified modelling strategy for spatial dependence and the dynamics of the whole income distribution.

However, before adopting spatial econometric techniques to the issue of risk sharing, researchers should extend existing theoretical models to directly incorporate spatial linkages of capital, federal government, and credit market smoothing, so that testable empirical implications can be derived from a sound theoretical basis. In growth theory, the connection between spatial econometric techniques and theoretical (structural) models including spatial linkages is beginning to attract increased attention (see for example Fingleton and López-Bazo, 2006). For the issue of risk sharing, we leave these interesting tasks to future research.

## 4.6 Conclusion

This paper focused on two related questions: First, to what extent do private institutions and the public sector provide insurance against idiosyncratic output shocks to individual regions? Second, to what extent do private institutions and the public sector reduce long-term differences in the relative position of a region reflecting its economic development relative to the national average?

It is unnecessary to emphasize that the aim of this study was not to draw conclusions about whether the existing federal transfer system redistributes too much or too little. Moreover, it is beyond the scope of this paper to analyze any negative incentive effects that can result from the fiscal transfer system. Instead, we were only interested in analyzing the stabilizing effects and predicting the long-term redistributive effects of fiscal transfers in reunified Germany.

Our empirical results suggest that private factor income flows provide almost complete insurance against region-specific shocks. A co-movement of income and output is only found for high and low idiosyncratic output risk. This pattern could not be detected within a linear regression approach which, in our application, tends to overstate the degree of insurance provided by private markets.

By sharp contrast, the federal government channel is not found to have a stabilizing effect on regional incomes. Rather than providing insurance against idiosyncratic shocks, fiscal transfers in reunified Germany are mainly concerned with redistribution in favor of depressed regions. The fiscal transfer system achieves a substantial reduction of long-term disparities between regions. If past distribution dynamics continue operating unchanged in the future, a uni-modal distribution of regional incomes will not be achieved without redistribution by the public sector. These findings imply that the public sector provides insurance against that type of risk which cannot be completely insured on private markets: The risk of being a permanently poor region.

Our paper shows that the patterns of short-term risk sharing (smoothing of shocks) and long-term redistribution of the public sector (smoothing of differences in levels) can differ substantially. Under the current law in Germany, it is hard to argue that short-term risk sharing is the main justification of the federal transfer mechanism. Though, previous studies on interregional risk sharing argue that even a redistributive policy may turn out to have stabilizing effects. In the US, 13 percent of shocks to gross state product are smoothed by the federal government (ASY, 1996). Using a similar approach as ASY (1996) to estimate the smoothing of state-specific shocks to West German states from 1970 to 1997, Buettner (2002) finds that the share of shocks to state income absorbed by fiscal flows is roughly at the same level as in the US. In reunified Germany, however, stabilization is not a by-product of fiscal redistribution at all, at least at the disaggregated regional level used in this paper.

# Chapter 5

# Home Bias, Neighborhood Bias, and Incomplete Capital Market Risk Sharing among US Federal States

## 5.1 Introduction

The gains from international diversification are well-documented.[1] If agents have access to a complete market for financial assets, then they can, by pooling their risk, insure fully against the idiosyncratic uncertainty in their resources. At the macroeconomic level, the idiosyncratic uncertainty in resources is reflected by fluctuations in idiosyncratic output. Aggregate output risk, by contrast, cannot be insured at the capital market. In the extreme case of full insurance against idiosyncratic output risk, the value of output is fully pooled through cross-ownership of productive assets and all agents hold an identical 'world' mutual fund of securities to insure against idiosyncratic output fluctuations.

At the macroeconomic level, we may think of the 'world' mutual fund as a perfectly diversified portfolio of so-called Shiller-securities, following the ideas brought forward by Shiller (1993). Shiller-securities have returns that are directly linked to the growth of output, which means that these assets comprise perpetual claims to the entire output stream of a country or region. Countries or regions can then sell the right to their own output and invest the proceed in

[1] See for example Grubel (1968), Solnik (1974), Eldor, Pines, and Schwartz (1988), DeSantis and Gerard (1997), and Shawky, Kuemzel, and Mikhail (1997).

claims to output of other countries (Sørensen, Wu, Yosha, and Zu, 2005). If each country is going short in the claims to its own output, output risk is shared via the identical 'world' mutual fund of Shiller-securities (Kalemli-Ozcan, Sørensen, and Yosha, 2004).

It is, however, observed that investors tend to ignore foreign investment opportunities. This means that actual portfolios deviate substantially from the benchmark of the perfectly diversified fund of Shiller-securities. There is a strong preference for domestic equities, which is at odds with the diversification of risk. This observation is referred to as the 'home bias' puzzle in equity holdings, see for example French and Poterba (1991), Tesar and Werner (1995), and Lewis (1999). At the same time, it is well-documented that international risk sharing among OECD countries is rather scarce, see for example Sørensen and Yosha (1998), Asdrubali and Kim (2004), or Becker and Hoffmann (2006).

Recent research by Sørensen, Wu, Yosha, and Zu (2005) and Artis and Hoffmann (2005) has shown that the 'home bias' puzzle is directly related to the apparent lack of international risk sharing. These papers show that risk sharing from international cross-ownership of assets is higher in countries that hold a higher amount of foreign equity, i.e., countries that are subject to less home bias enjoy more risk sharing. Hence, the apparent home bias in international investment portfolios is one explanation why risk sharing among OECD countries is only scarce—in fact, the channel of capital market risk sharing has been virtually absent until the early 1990s.

At the regional level, we would expect that biases in capital income flows manifest themselves in a more complex way than a pure home bias. In particular, we would expect that regional asset portfolios are characterized by a disproportionate high fraction of assets issued in geographically close areas—but not necessarily the home region.

Indeed, there is considerable evidence from micro-based studies which analyze individual investment portfolios directly that the home bias within a country manifests itself in such a complex way (see Coval and Moskowitz, 1999, and Huberman, 2001). Therefore, we may think of the home bias within a country in more general terms as a 'local bias', which may consist of a pure 'home bias at home', but also of a 'neighborhood bias'. We interpret this 'neighborhood bias' as a bias which is related to economic distance and geographical proximity. The aim of this paper is to examine a potential neighborhood bias within the US and its consequence for the overall amount of income risk sharing that is achieved among US federal states.[2]

In the presence of both, a home bias 'at home', but also a 'neighborhood bias', the home state's idiosyncratic income does not only co-move with idiosyncratic output shocks to the home state, but also with shocks that hit neighboring states. Taking into account a potential neighborhood bias in capital income flows may lead to a more qualified picture of capital market risk sharing within the US. Even if own idiosyncratic output shocks are comparatively well insured—as it has been suggested by previous studies—the welfare effects of income fluctuations caused by output shocks in geographically close states may be non-negligible if there is a pronounced neighborhood bias.

Unfortunately, a direct-attack approach to estimating the home bias and neighborhood bias across US federal states is not possible. Data on the composition of regional asset holdings across US federal states is simply not available—as it is not for many other countries. Going back to the micro-level and analyzing individual asset holdings directly seems not a proper solution since our interest is not only in regional portfolio diversification, but also in its consequences for aggregate (regional) risk sharing.

Instead, we propose an alternative solution which allows us to address the neighborhood bias and risk sharing at the regional level: we extend the standard risk sharing model to a spatial model. One particular advantage of the spatial modelling strategy is that we can estimate our model using the same macroeconomic data that is usually used to study risk sharing among US federal states.[3]

This spatial model allows us to examine whether the fluctuation of *factor income flows* between states and their neighbors is disproportionately high—in comparison to a balanced portfolio which assigns fair weights to each others output. Or to put it differently, we take the perspective of an average federal state and provide evidence whether its neighbor's output fluctuation also constitutes a risk factor which is transmitted to the home state's idiosyncratic income via factor income flows.[4]

[2] In the next section, we discuss the issues of home bias, neighborhood bias, and capital market risk sharing in more detail. We also present some theoretical considerations which have been put forth to explain the home bias phenomenon and which should similarly apply for the phenomenon of a neighborhood bias.

[3] See for example Asdrubali, Sørensen, and Yosha (1996), Sørensen and Yosha (1998), Mélitz and Zumer (1999), Athanasoulis and van Wincoop (2001), Asdrubali and Kim (2004), Asdrubali and Kim (2005), Kalemli-Ozcan, Sørensen, and Yosha (2004), Becker and Hoffmann (2006).

[4] On the one hand, a neighborhood bias may constitute additional risk but at the same time it may also induce additional insurance, because a limited amount of diversification takes places. We will take this ambiguous role of the neighborhood bias into account.

Factor income flows comprise capital income flows between states, such as dividends from cross-holdings of productive assets. Therefore, factor income flows determine the amount of capital market risk sharing that is achieved. Especially at the regional level, however, factor income flows do also reflect income flows associated with the factor labor. For instance, if workers commute to their place of work in another federal state, their output is measured at their place of work while their income is attributed to their place of residence. Therefore, our analysis will account for commuter flows across states in order to test whether a neighborhood bias in factor income flows is indeed a phenomenon which should be attributed to the capital market (i.e., reflects a neighborhood bias in portfolio holdings), or if labor income flows also play a role.

The aims of this paper are therefore twofold. Firstly, we want to quantify how strongly a potential neighborhood bias in factor income flows influences the overall amount of income insurance that is achieved among US federal states. Secondly, we want to examine which economic factors drive the neighborhood bias in factor income flows.

The paper is structured as follows. In the next section we present a brief introduction to the issue of capital market risk sharing and we motivate our analysis of local biases from a theoretical point of view. Our spatial model of capital market risk sharing is presented in the third section. In the fourth section, we estimate the neighborhood bias in factor income flows among US federal states and its consequences for the overall degree of income risk sharing. Thereafter, we extend the analysis to include commuter flows in order to test whether the neighborhood bias can be explained by commuting across state-borders. In Section 6, we discuss some extensions for future work. The last section summarizes our main findings.

## 5.2 Risk sharing, factor income flows, and local biases

### 5.2.1 Risk sharing through factor income flows

At the heart of interregional risk sharing stand the fundamental differences between state-level Gross Domestic Product (GSP) and state-level income. While GSP corresponds to a state's production and hence attributes to a state the amount of economic production generated within it, income explicitly includes net factor payments from other states. Thus, income equals output plus net factor income flows.

The general idea of capital market risk sharing is that, by holding claims to output produced in other regions, individuals can smooth away shocks to their own income caused by variations in their home region's production. This means that individuals can share their output risk by diversifying their asset portfolios, i.e., via cross-ownership of productive assets.

There is a substantial literature studying the amount of risk sharing within the US.[5] The overall pattern of risk sharing among US federal states is generally found to be much richer than that for international risk sharing. Most studies agree that in the US, a considerable amount of income smoothing takes place via capital markets, indicating that much of a state's product is owned by residents of other states. This cross-ownership of productive assets provides important hedging against idiosyncratic output shocks. Previous studies report that, on average, almost 40%-50% of an idiosyncratic shock to output is smoothed via cross-state capital income flows.

In the National Accounts data, cross-state capital income flows are reflected as the difference between GSP and income. However, the difference between GSP and income also reflects retained earnings in the form of capital depreciation and corporate saving, and commuters income. Athanasoulis and van Wincoop (2001) argue that retained earnings do not alter the economic interpretation of capital market risk sharing substantially because retained earnings reflect an investment that contributes to dividends in the future.

However, claims to labor income (and also other non-tradable output components) can hardly be insured at the capital market. Especially at the regional level, commuting across state borders is also a way of hedging idiosyncratic output risk because it allows individuals to insure their human capital risk. For instance, if workers commute from their place of living to their place of work in a neighboring federal state, they contribute to the output of the neighboring state while their income crosses state borders. In other words, output is measured at the place of work, while income is measured at the place of residence. This means that the wedge between output and income is not driven by capital markets solely.[6] At the same time, this means that a potential neighborhood bias in factor income flows does not necessarily reflect a neighborhood bias in

[5] For a recent overview we refer to Kalemli-Ozcan, Sørensen, and Yosha (2004). For more details, see the cited studies in footnote 3.

[6] According to the author's view, this aspect has been largely ignored in the literature. While commuter flows may be of minor importance for the international economy, they should not be ignored in the context of an interregional study. As it will turn out, risk sharing among US federal states is indeed driven substantially by commuter flows.

portfolio holdings.

Keeping this important point in mind, we turn to a deeper discussion of the issues of risk sharing and biases in *capital* income flows, because these issues have been examined in considerable detail in the literature—in contrast to the issue of risk sharing through commuting.

### 5.2.2 Risk sharing and biases in capital income flows

A general interpretation of capital income flows between regions is that individuals own *claims to output* produced in other regions. The risk sharing literature (see for example Artis and Hoffmann, 2005) refers to these perpetual claims to the state's entire output stream as Shiller-securities (Shiller, 1993), which have returns that are directly linked to the growth of GSP in a state. Although Shiller-securities are not actually traded in reality, many assets in real-life can be thought of having very similar properties, see Artis and Hoffmann (2005) and Sørensen, Wu, Yosha, and Zu (2005) for brief discussions.

A non-exclusive list of financial instruments through which diversification can occur in reality includes corporate equity, direct investment, real estate, bank deposits, trade on forward markets, and investment in bonds and shares. For instance, if mutual funds or pension funds in one region invest in other regions, the income of the citizens in that state includes factor income from other regions and will partly co-move with the output in other regions. Another example is that if financial intermediaries in one state lend to firms in other states, the flow of interest payments smooths the income of citizens in the lending state (these examples have been taken from Kalemli-Ozcan, Sørensen, and Yosha, 2004, p. 5).

In a world with full information, no moral hazard, no trading cost, and the same degree of risk aversion across agents, all agents should hold an identical 'world' mutual fund of Shiller-securities to insure against idiosyncratic output uncertainty. The financial literature typically motivates this 'world' market portfolio from the benchmark of the international Capital Asset Pricing Model (CAPM). In terms of the CAPM, the identical market portfolio implies that all agents have similar mean-variance utility trade-offs (see Sørensen, Wu, Yosha, and Zu (2005) and Huberman (2000) for a brief survey of the literature on CAPMs).

Clearly, this world portfolio—or US-wide portfolio in our setting—is the optimally diversified portfolio. If agents hold this optimal portfolio of Shiller-securities, a state's income is then just the weighted average of all per capita output, whereas the weights capture the size of the population in the different states. This weighting reflects that it is optimal to own more claims to the *per capita* output of larger states than to the *per capita* output of smaller states. With CRRA utility and a common intertemporal discount factor for all federal states, perfect income risk sharing implies that state-level income per capita is a constant fraction of aggregate income in the US as a whole—independent of uncertainty.

In a nutshell, the central empirical implication of full capital market risk sharing is that the value of idiosyncratic output per capita is fully pooled through financial cross-ownership, i.e., through capital income flows across state borders, and this pooling should be independent of neighboring relationships among states.[7]

However, if there is a local bias in portfolio holdings—either in the form of home bias or neighborhood bias—full risk sharing is not achieved. Clearly, some explanations which have been put forth to explain the home bias are unique to the international economy. For instance, when capital crosses political and monetary boundaries, it faces exchange rate fluctuation and variation in regulation, culture, taxation, and sovereign risk.[8] Within the US, by contrast, there is relatively little variation in regulation, taxation, and political risk.

As emphasized by Coval and Moskowitz (1999), however, not all home bias explanations are unique to the international economy. Most prominent frictions which also arise even in the absence of country borders are information asymmetries, the concern for hedging non-tradable goods, and familiarity biases which are related to behavioral explanations. Since those frictions are related to geographic distance one would expect that they should also play an important role for the neighborhood bias, i.e., for a local bias in portfolio holdings which is related to economic distance and geographical proximity.

For instance, investors may have superior access to information about firms located near to them or about local economic conditions. For the home bias in international capital markets, such asymmetric information-based explanations have been offered, among others, by Coval (1996), Brennan and Cao (1997), Zhou (1998), Hatchondo (2004), and Ahearne, Griever, and Wanrock (2004).

[7] If idiosyncratic output risk is not fully shared through capital market linkages, there is scope for further consumption smoothing through savings behavior. This intertemporal consumption smoothing may further buffer consumption from income fluctuations (see for example Becker and Hoffmann, 2006, and Artis and Hoffmann, 2005). In this paper the focus is on capital market risk sharing. The issue of credit market risk sharing is left to future research, see the outlook in the Section 7.

[8] See Lewis (1999), Huberman (2000), and Karolyi and Stulz (2003) for extensive discussions why actual portfolios may deviate from the benchmark of the international CAPM.

The empirical studies of Portes and Rey (2000, 2005) also suggest that information asymmetries across countries are a major source of home bias effects, and that capital flows are affected by both, geographic distance and informational proximity. Similarly, Tesar and Werner (1995, p. 485) summarize that 'geographic proximity seems to be an important ingredient in the international portfolio allocation decision'. In line with this, Kilka and Weber (2001) show that investors tend to perceive the domestic market as less volatile than foreign markets.

These factors should be of particular importance within a domestic setting. Indeed, the seminal paper of Coval and Moskowitz (1999) finds that US investment managers exhibit a strong preference for locally headquartered firms and that US investors hold more than a proportional amount of assets issued in the geographical region close to them. Specifically, distance is found to play an important role in determining the composition of asset portfolios. Therefore, Coval and Moskowitz (1999) suggest that an information advantage in local stocks is also an explanation for the preference for geographically proximate investments within the US.[9]

Huberman (2000, 2001) argues that a cognitive bias for the familiar may play an important role in explaining local biases in the US. The preference for investing close to one's home may be driven by a psychological desire to invest in local companies. Possibly, agents simply feel comfortable investing in a business that is visible to them and therefore overweigh investments close to their place of living. Moreover, investors may have to learn about risk sharing and therefore try to gain experience by buying assets which are closely related to their home region. In line with this, Strong and Xu (2003) find that fund managers are relatively more optimistic about investment possibilities in their home markets.[10]

Against the background of these theoretical considerations, an analysis of a potential neighborhood bias in capital income flows appears interesting even without introducing a formal theoretical model. This makes the focus of this

[9] However, Huberman (2000) criticizes arguments based on asymmetric information. Specifically, Huberman points out that uninformed investors can still buy an *index* of the equities about which they know very little. Moreover, superior information is usually short-lived. Lastly, being better informed will induce many 'buy' opportunities, but also many 'sell' opportunities.

[10] An alternative explanation for local bias is that individuals try to hedge non-traded goods by holding local assets. By holding proximate investments, individuals can hedge against price increases in local services or in non-traded goods. However, researchers have not found much evidence for this hypothesis, see Cooper and Kaplanis (1994) and Pesenti and van Wincoop (2000).

paper an empirical one. In particular, we want to quantify how strongly a potential neighborhood bias influences the overall amount of risk sharing that is achieved among US federal states.

## 5.3 A spatial model of capital market risk sharing

### 5.3.1 Summary of the empirical strategy

Before we formalize our empirical model to measure risk sharing and a potential neighborhood bias in factor income flows, we summarize the general idea of our approach.

If idiosyncratic output risk is fully shared among a group of regions, then a region's income should be affected only by aggregate fluctuations in output. Other things such as an idiosyncratic shock that hits the region's output or idiosyncratic shocks to other regions should not be transmitted to idiosyncratic income. In our empirical model we allow for both, output shocks that hit the home region and output shocks to neighboring regions. The latter shocks are measured by the weighted average output fluctuation in neighboring states—in idiosyncratic and per capita terms.

The test for no local bias towards these neighboring states is then straightforward. If factor income flows are not subject to a neighborhood bias, i.e., if agents prefer a balanced and diversified portfolio, then any change in idiosyncratic output of neighboring states should have no influence on idiosyncratic income of the home state.

For instance, if idiosyncratic output growth of neighboring states is positive, factor income flows to the home state and hence the home state's income increase due to increased returns of Shiller-securities issued in those neighboring states—but this effect shows only part of the picture. The positive idiosyncratic output growth of neighbors must by construction be offset by a negative idiosyncratic output growth of other, non-neighboring states.[11]

Under the assumption that the cross-ownership of productive assets is balanced, both effects cancel out and the idiosyncratic income of the home state remains unchanged. If, by contrast, we find a positive effect of the increase in neighbor's idiosyncratic output on the home states' idiosyncratic income, this

[11] Holding constant aggregate risk, the sum of idiosyncratic ouput risk equals zero by construction (accounting for population weights).

implies that the citizens of the home state own a disproportionate large fraction of claims to output produced in neighboring states.[12]

### 5.3.2 Model specification

Let $inc_{it}$ and $gsp_{it}$ denote state $i$'s year $t$ real per capita income and output, respectively. The real and population-weighted average per capita income and output for the US as a whole are denoted as $inc_t^*$ and $gsp_t^*$. All data has been transformed to real figures by dividing by the US-wide Consumer Price Index (CPI).

The key variables in our study are the state's logarithmic or percentage deviations from the US-wide average per capita values of production and income:

$$\begin{aligned} y_t &= \log inc_{it} - \log inc_t^* \\ x_t &= \log gsp_{it} - \log gsp_t^*. \end{aligned}$$

To keep the notation as simple as possible we omit the index $i$ for the states and denote stacked vectors as $y_t$ and $x_t$ (instead of $y_{it}$ and $x_{it}$). Throughout the paper, we refer to the variables $y_t$ and $x_t$ as 'relative' or 'idiosyncratic' variables.

A direct approach to measuring risk sharing at the regional level is to consider the following set of cross-sectional regressions (one regression for each year $t$):

$$\Delta y_t = \alpha_t + \beta_{K,t} \Delta x_t + \varepsilon_t, \tag{5.1}$$

where $\alpha_t$ denotes a constant term and $\varepsilon_t$ a white-noise error term (also in stacked form).[13] The risk sharing coefficient $\beta_{K,t}$ measures the average co-movement of the regions' idiosyncratic income growth with their idiosyncratic output growth in year $t$. The smaller the co-movement, the more income is buffered against own output fluctuations. If income smoothing is perfect then idiosyncratic income $y_t$ does not co-move with idiosyncratic output $x_t$ at all and the coefficient $\beta_{K,t}$ takes the value 0. In the situation with no risk sharing, income moves one-to-one with output and $\beta_{K,t} = 1$. We follow the literature in defining $(1 - \beta_{K,t})$ as our measure of risk sharing through interregional factor income flows. Thus, if no state-specific risk is hedged we find $\left(1 - \beta_{K,t}\right) = 0$.

[12] The effect of commuter flows will be taken into account in the next section.

[13] This risk sharing regression or similar variants have been conducted, among others, by Asdrubali, Sørensen, and Yosha (1996), Sørensen and Yosha (1998), Mélitz and Zumer (1999), Becker and Hoffmann (2006), and Sørensen, Wu, Yosha, and Zu (2005).

It is also possible to pool the data and to estimate equation (5.1) as a panel data model:

$$\Delta y_t = \pi_i + \beta_K \Delta x_t + \varepsilon_t. \tag{5.2}$$

In equation (5.2), $\pi_i$ denotes fixed effects which capture unobserved heterogeneity among states, e.g. non time-varying differences in growth performances.[14] The common slope parameter $\beta_K$—more precisely $(1-\beta_K)$— can be interpreted as the average amount of capital market risk sharing during the sample period, see the paper of Asdrubali, Sørensen, and Yosha (1996) for a discussion.

The novelty of this paper is to consider an extended risk sharing regression which also takes into account the effect of the idiosyncratic output growth of neighboring states. This spatial extension of the risk sharing regressions (5.1) and (5.2) allows us to shed light on a potential neighborhood bias in factor income flows.

The cross-sectional variant of our spatial risk sharing model reads as:

$$\begin{aligned} \Delta y_t &= \beta_{K,t} \Delta x_t + \beta_{N,t} \Delta \tilde{x}_t + u_t, \\ u_t &= \rho_t W u_t + \varepsilon_t. \end{aligned} \tag{5.3}$$

The additional regressor $\Delta \tilde{x}_t$ is designed to measure the weighted average idiosyncratic output shock (in per capita terms) in neighboring states. To illustrate how this variable is constructed, we can consider as an example one element $k$ of the vector $\tilde{x}_t$.

Dropping the time index $t$ for simplicity, this element $\tilde{x}_k$ can be written as

$$\tilde{x}_k = \frac{\sum_{i \epsilon N_k} b_i \cdot x_i}{\sum_{j \epsilon N_k} b_j}. \tag{5.4}$$

In this expression, $N_k$ comprises all states which are neighbors to state $k$. The term $b_i$ denotes the population size of state $i$. Hence, the numerator $\sum_{i \epsilon N_k} b_i \cdot x_i$ is the sum of (idiosyncratic) output produced in neighboring states—in absolute, not in per capita terms. The total idiosyncratic output of neighboring states is divided by the total population in those states. Thus, the variable $\Delta \tilde{x}_k$ measures the average idiosyncratic output change in neighboring states, expressed in per capita terms. As we will explain in more detail below, we will test the hypothesis

[14] There is no need to include time fixed-effects because our variables are already formulated relative to the national average.

that $\beta_{N,t} = 0$. If $\beta_{N,t} \neq 0$, this means that factor income flows between states are subject to a neighborhood bias.

The regressor $\Delta\tilde{x}_t$ is a so-called 'spatial lag' of $\Delta x_t$. We draw from spatial econometric techniques to compute (5.4). Usually, a spatial lag of some variable is computed by pre-multiplying this variable by a matrix $W$. The matrix $W$ is a known $i \times i$ spatial weighting matrix which contains the neighboring relationships among the $i$ regions. In the simplest case, the matrix $W$ defines the binary contiguity relationships of neighbors. This means that in the matrix $W$ values of unity are placed in positions $i, j$, where $j$ indicates regions that have borders touching region $i$.

We experiment with several possibilities to construct the contiguity matrix $W$. A common method is based on polygon centroid coordinates. These coordinates can be used to produce an adjacency matrix from so called 'Delaunay triangles'. Another possibility to construct $W$ is to find a certain number of nearest neighbors to each region. In any case, the matrix $W$ has entries of zeros for non-neighbors and ones for neighbors, with zeros on the main diagonal.

In order to match the definition (5.4) of $\tilde{x}_k$ we additionally have to assign *population-based* geographic weights to each neighbor. This means that larger neighboring states must be given more weight than smaller ones. To illustrate the need for a proper weighting we can consider the neighboring relationships for a specific state, say Nevada, as an example. Assume that the neighborhood criterion has assigned five neighbors to Nevada. If we were not to assign population weights to each neighbor, we would assume that it is optimal to hold the same amount of claims to output in each neighboring state, irrespective of the size of the states. Such investment, however, is not optimal. The neighboring states with a large population, such as California, should get a large portfolio weight. Thus, our population-based geographic weights capture the optimal portfolio weights of Shiller-securities.

We therefore construct a $i \times i$ matrix of the state's population size which is denoted as $B_t$. The columns of $B_t$ contain the population size of the states. All rows of $B_t$ are the same, which means that the row containing the different population values is stacked one below the other.[15] Since the population of each state changes over time, also the matrix of the state's population (weights) $B_t$ is not constant. Therefore, we compute a matrix $B_t$ for each year in the sample.

An element-wise multiplication of the matrices $W$ and $B_t$ yields a weighting matrix that takes into account the population-weights. By construction, the

[15] It does not matter whether the matrix $B_t$ contains the absolute population size of the states or their population weight, i.e. their relative population size. If one uses population

sum of all population weights is one, but the sum of all population weights for neighbors is smaller than one, since neighboring states are only a subset of all US states. Therefore, the last step in constructing the final weighting matrix is to standardize the element-wise matrix product $[WB_t]$ so that the row sums equal unity.

The matrix product of the standardized matrix $[WB]$ and the regressor $x_t$ then produces an average of the idiosyncratic output shocks of states meeting the definition of neighbors. This allows us to rewrite our spatial risk sharing model in terms of the idiosyncratic output shock $x_t$ by replacing the spatial lag $\Delta\tilde{x}_t$ with the matrix product $[WB_t]\Delta x_t$ :

$$\begin{aligned} \Delta y_t &= \beta_{K,t}\Delta x_t + \beta_{N,t}[WB_t]\Delta x_t + u_t, \\ u_t &= \rho_t W u_t + \varepsilon_t. \end{aligned} \tag{5.5}$$

The error term $u_t$ is assumed to follow a spatial moving average process. This error process may capture further spatial autocorrelation which is not eliminated through the inclusion of our spatial regressor $[WB_t]\Delta x_t$. In the next section we will provide empirical evidence that the spatial error specification is indeed more appropriate than the assumption of a white noise error process. In equation (5.5), the parameters to be estimated are $\beta_{K,t}$, $\beta_{N,t}$ and $\rho_t$.

If we are not interested in the variation of the point estimates over time but in quantifying the average amount of risk sharing during a specific sample period, we can pool the data and estimate the $\beta$ coefficients and $\rho$ from a panel data model:

$$\begin{aligned} \Delta y_t &= \pi_i + \beta_K\Delta x_t + \beta_N[WB_t]\Delta x_t + u_t, \\ u_t &= \rho W u_t + \varepsilon_t. \end{aligned} \tag{5.6}$$

Elhorst (2003) has developed a Maximum-Likelihood estimator for static panel data models with fixed effects $\pi_i$ and a spatial error process $u$. We will use this estimator to estimate (5.6).

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weights instead of the absolute population size, equation (5.4) reads as

$$\tilde{x}_k = \frac{\sum\limits_{i \epsilon N_k} \frac{b_i}{\sum\limits_s b_s} \cdot x_i}{\sum\limits_{l \epsilon N_k} \frac{b_l}{\sum\limits_s b_s}},$$

whereas the sum running over the index $s$ contains all states in the sample, not only neighbors to state $k$. This definition of $\tilde{x}_k$ is equivalent to (5.4).

## 5.4 Estimating risk sharing and the neighborhood bias

### 5.4.1 Data

The state-level data used in this study is the same as the data constructed by Asdrubali, Sørensen, and Yosha (1996) and we refer to their data appendix for an extensive description on how the data is constructed. This data has also been used, among others, by Mélitz and Zumer (1999), Crucini and Hess (2000), Athanasoulis and Wincoop (2001), Asdrubali and Kim (2004a), Asdrubali and Kim (2004b), Sørensen, Wu, Yosha, and Zu (2005), and most recently by Artis and Hoffmann (2005) and Becker and Hoffmann (2006). In the meantime, the database constructed by Asdrubali, Sørensen, and Yosha has been updated. While the aforementioned papers (those which are already published) use data for 1963-1990, our estimations refer to the extended sample period 1963-1998.[16]

One major advantage of this extended data is that it covers the period which is usually referred to as the 'globalization period'. After the 1980s, but especially after the 1990s, international financial markets have become increasingly integrated, see the discussion in Artis and Hoffmann (2005). Hence, we would also expect a change—in particular, an increase—in risk sharing among countries, but also among regions. For countries, this relationship has been corroborated by Artis and Hoffmann (2005). For US states, the paper by Kalemli-Ozcan, Sørensen, and Yosha (2004) provides updated evidence for the extended sample period 1963-1998. This is also the period of time examined in our paper.

Our empirical analysis takes data on Gross State Product and state income into account. State income as constructed by Asdrubali, Sørensen, and Yosha consists of personal income after substracting out all federal transfers and allocating all non-personal taxes to income. Further, income of state governments that is not derived from personal taxes is also included in state income (see Kalemli-Ozcan, Sørensen, and Yosha, 2002, footnote 27). Hence, one important feature of the income data constructed by Asdrubali, Sørensen, and Yosha (1996) is that it is adjusted for federal transfers and contributions. For the exact definition of the variables we refer to the original paper by Asdrubali, Sørensen, and Yosha (1996). Population data stems from the Bureau of Economic Analysis (BEA).

One difference to related studies is that we restrict the analysis to the 48 continental US states because we want to use a consistent concept of neighbors.

[16] I thank Mathias Hoffman for providing the data to me.

Previous studies included the full set of states in the analysis (including Hawai, Alaska, and sometimes Washington D.C.).

For the spatial contiguity matrix $W$ we tried several alternatives which we have discussed above, i.e. based on physical contiguity, Delaunay triangulization, and nearest neighbors. According to some pre-testing, our results are not exceedingly sensitive to the particular choice for $W$. For brevity, we will only present the results obtained with the contiguity matrix based on Delaunay triangles.

### 5.4.2 Cross-sectional analysis

To set the scene, we estimate the risk sharing models (5.1) and (5.5) year-by-year from the cross-sections of states. The aim of this exercise is to get a sense of the variation in the point estimates over time. The non-spatial model (5.1) is estimated with simple OLS while the spatial model (5.5) is estimated using the Maximum Likelihood estimator for spatial error models described in Anselin (1988).[17] Thereafter, we pool the data and turn to a panel estimation of models (5.2) and (5.6).

Figure 5.1 provides an overview about the estimation results of the risk sharing parameter $\beta_{K,t}$, which measures the co-movement of income with own output shocks. Each sub-plot contains two graphs. The thin line displays the sequence of $\beta_{K,t}$ obtained with the non-spatial model (5.1) while the thick line shows the estimates of $\beta_{K,t}$ from the spatial model (5.5).

The top panel in Figure 5.1 displays the raw point estimates of $\beta_{K,t}$. Since we are interested in the trend-movements in the series, we smooth the sequence of point estimates at neighboring time-periods (see the bottom panel in Figure 5.1).

The bottom-left panel displays the smoothed series of $\beta_{K,t}$ using a Normal kernel smoother. The bandwidth in the local linear regression has been selected by using the Ruppert, Sheather, and Wand (1995) Plug-In method.

As an alternative smoothing procedure we use the Hodrick-Prescott (1997) (HP) filter. Since our data are observed at annual frequencies we use a smoothing parameter of $\mu = 100$ for the HP-filter. This choice for $\mu$ is widely accepted

[17] As a robustness test, we also left out the spatial moving average process in the error term and estimated the spatial model (5.5) with simple OLS (the spatial regressor $[WB_t]\Delta x_t$ does not cause any problems for OLS since it is assumed to be exogenous). The point estimates of the $\beta$ coefficients turned out to be very similar across both estimations. This similarity reflects that OLS remains an unbiased estimator if the spatial dependence only affects the error term. The Maximum-Likelihood estimator, however, is more efficient than OLS in the presence of significant spatial autocorrelation.

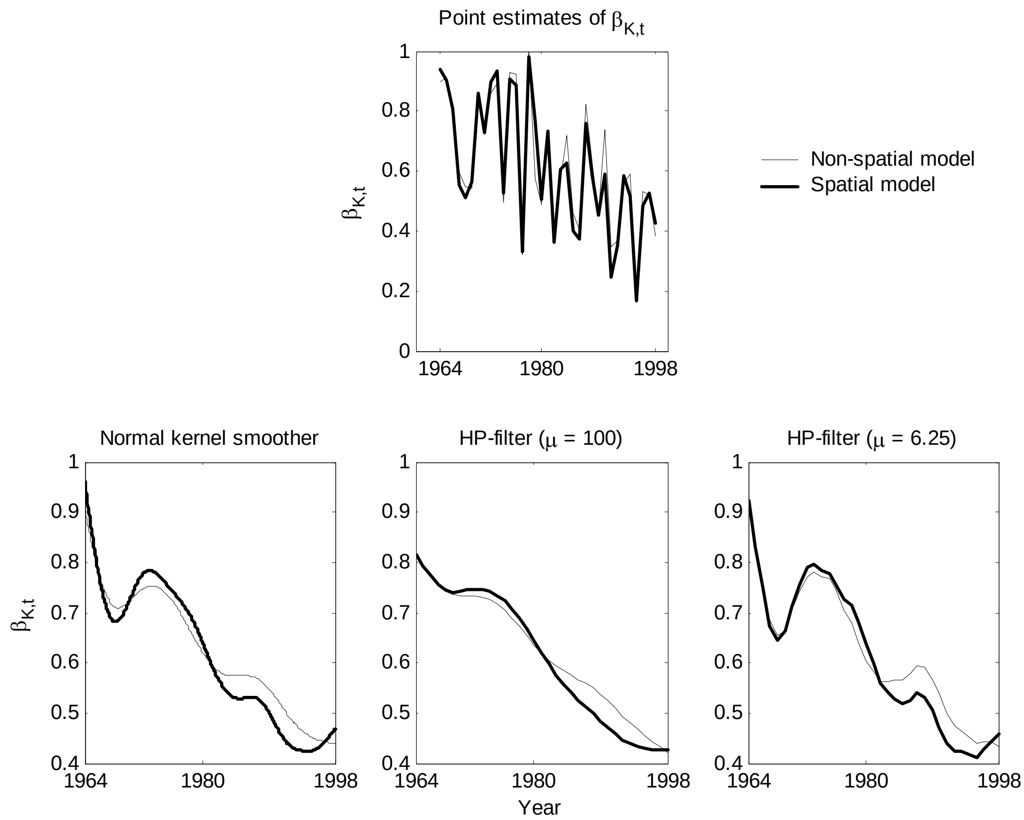


Figure 5.1: Capital market risk sharing of own idiosyncratic output shocks among US federal states, 1963-1998. Top: raw point estimates of $\beta_{K,t}$ against time. Bottom: smoothed sequences of $\beta_{K,t}$ against time.

in the business cycle literature. However, Ravn and Uhlig (2002) proposed a different smoothing parameter of $\mu = 6.25$ for yearly data. For the sake of completeness we tried both values for $\mu$. The remaining two subplots in the lower panel of Figure 5.1 present the results for the HP-filtered estimates.

Consider first the series of raw point estimates for $\beta_{K,t}$ (top). It can be seen that the degree of capital market risk sharing varies considerably over time. This variation seems to be driven by business cycle fluctuations but a deeper analysis of this issue is beyond the scope of this paper. Our primary focus will be on the smoothed series of $\beta_{K,t}$.

The graph obtained with the HP-filter and a smoothing parameter of $\mu = 100$ is the smoothest one (middle). The other graphs appear to be somewhat undersmoothed. Therefore, we regard the results obtained with the HP-filter and a smoothing parameter of $\mu = 100$ as our preferred ones. It should be noted that the general pattern of the variation of the point estimates over time is quite similar across the different procedures to smooth the point estimates.

In particular, there are two main facts which emerge from Figure 5.1. First, insurance against own idiosyncratic output fluctuations increases substantially over time, as reflected by the decline in $\beta_{K,t}$. Second, the estimated amount of risk sharing is very similar across the non-spatial and spatial specifications.

In both models, the $(1 - \beta_{K,t})$'s measure the percentage of smoothing of a state's GSP shock carried out by capital markets and we expect $\beta_{K,t} = 0$ if there is full risk sharing through capital income flows. If $\beta_{K,t}$ is taken from the spatial model (5.5) the parameter has to be interpreted conditional on the assumption that the idiosyncratic output of neighbors remains unchanged.

In the early 1960s only about 20 percent of an idiosyncratic output shock is smoothed by capital income flows. Starting off from this low level, interstate risk sharing has increased substantially over time. Until the 1990s, there has been a steady positive trend in the risk sharing parameter $(1 - \beta_{K,t})$ up to a level of about 50-60 percent. This means that today only 40 percent of an idiosyncratic shock to the GSP of individual states are not insured through the capital market channel.

These estimates are well in line with those numbers which have been reported in previous studies. We can compare our cross-sectional results in particular to the ones documented in Kalemli-Ozcan, Sørensen, and Yosha (2004). This paper discusses that the apparent increase in insurance through interstate capital income flows is indeed statistically significant and not due to pure sampling variation.

Concerning our two different models to estimate the sequence of $\beta_{K,t}$, we find that the estimates are quite similar across the non-spatial and spatial specifications. After the 1980s, the spatial model yields a higher degree of risk sharing than the non-spatial one, i.e., the $\beta_{K,t}$'s for the spatial model are closer to zero than the ones for the non-spatial model. The overall pattern of smoothing of own output risk, however, is found to be the same across both models.

In order to motivate the spatial moving average specification in the error term of our extended risk sharing model (see equation (5.5)), we analyze the residuals of the non-spatial model (5.1). We test for spatial autocorrelation in the residuals $\varepsilon_t$ of each cross-sectional regression by performing a Moran's I test on the residuals. To save on space, we only discuss the overall result of this exercise. In about half of all years (51 percent) the Moran's I test statistic is significant at least at the 10 percent level. This means that the null hypothesis of no spatial autocorrelation is rejected for half of the cross-sectional regressions.

Hence, besides our economic motivation to test for a potential neighborhood bias there are also fundamental statistical reasons to account for spatial dependence in models of the type (5.1). The spatial moving average process in the error term (see equation (5.5)) captures any remaining spatial autocorrelation which is not eliminated by including the spatial regressor $[WB_t]\Delta x_t$. In most time periods, the estimate for the spatial autocorrelation coefficient $\rho$ is significantly different from zero, as we would expect from the test results obtained with Moran's I test. We do not report the point estimates for $\rho$ since this nuisance parameter is not in the focus of our paper. More details concerning the magnitude of $\rho$ will become apparent from the panel-based estimations in the next sub-section.[18]

The overall picture suggested by the cross-sectional regressions is that, although insurance among US states is considerable, the hypothesis of *full* risk sharing ($\beta_{K,t} = 0$) is clearly rejected. The still large amount of idiosyncratic risk which is not diversified indicates that US states are subject to some form of home bias, in a sense that regional portfolios seem to deviate substantially from the perfectly diversified portfolio which would lead to perfect risk sharing and $\beta_{K,t} = 0$. An inspection of the parameters $\beta_{N,t}$ sheds light on the question whether a potential neighborhood bias in factor income flows constitutes an additional risk factor which influences the overall degree of income insurance.

Similar to the risk sharing coefficient $\beta_{K,t}$, this parameter should be zero if no neighborhood bias is driving interstate factor income flows. An extreme case might be helpful to illustrate this. If risk sharing is complete and agents hold perfectly diversified portfolios of Shiller-securities, for each state income growth equals the US-wide income growth. Then, *both* coefficients $\beta_{K,t}$ and $\beta_{N,t}$ take the value 0 simply because the left-hand side of equation (5.5) is always 0.

Figure 5.2 summarizes the estimation results for $\beta_{N,t}$ obtained with the spatial risk sharing model (5.5). In order to illustrate the joint development of $\beta_{N,t}$ and $\beta_{K,t}$ over time, we also include the HP-filtered series of $\beta_{K,t}$ as a thin line in the graphs.

While the raw point estimates of $\beta_{N,t}$ fluctuate considerably (top), the smoothed series (bottom) suggest more clearly that the overall development of $\beta_{N,t}$ may be divided into two (or three) sub-periods. During 1963-1980, the point estimates for $\beta_{N,t}$ fluctuate around zero and are small in absolute terms. In fact, for most of these estimates we cannot reject the hypothesis that they

[18] The finding of spatial dependence in US state-level data is well in line with studies which focus on the consequences of spatial interaction effects on convergence analyses. For instance, the study of Rey and Montouri (1999) provides strong evidence of positive spatial dependence in both, levels and growth rates of income per capita in the US.

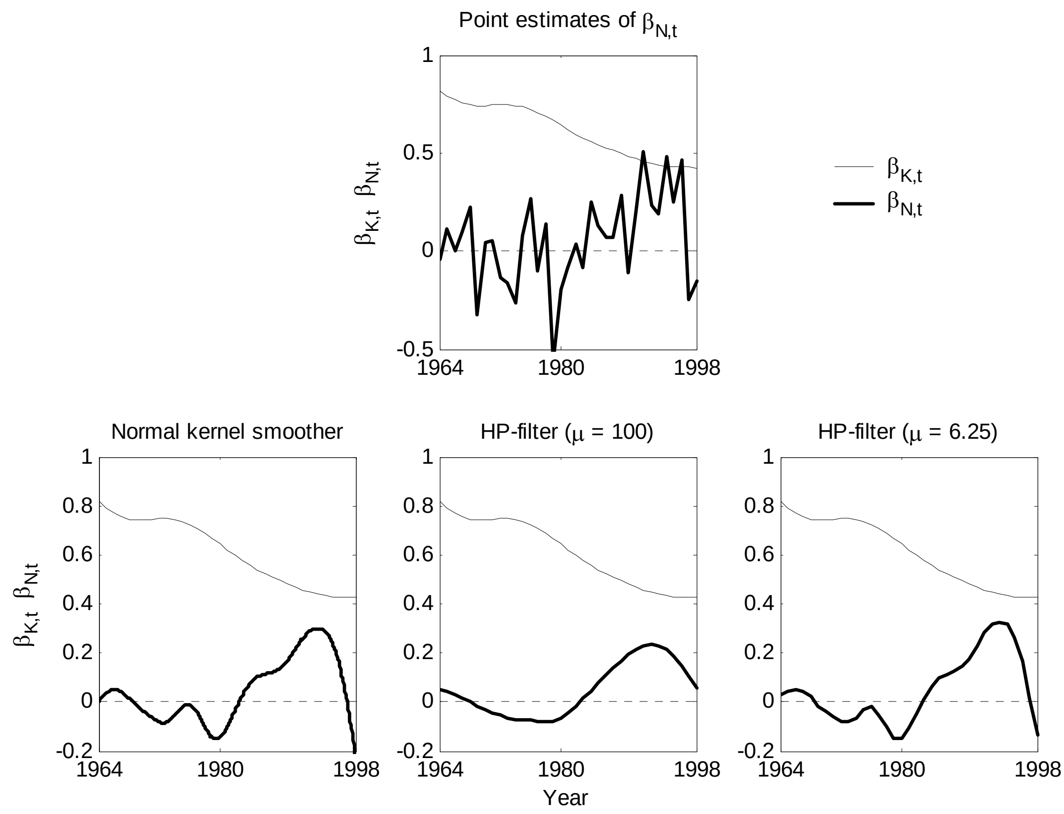


Figure 5.2: Bold line: neighborhood bias in factor income flows among US federal states, 1963-1998. Thin line: smoothed sequence of $\beta_{K,t}$ against time, see Figure 5.1. Top: raw point estimates of $\beta_{N,t}$ against time. Bottom: smoothed sequence of $\beta_{N,t}$ against time.

are zero. Thus, during the first sub-period interstate factor income flows are not subject to a substantial neighborhood bias. By contrast, the point estimates for $\beta_{N,t}$ are larger during the second sub-period 1980-1998. What can also be seen from Figure 5.2 is an increase followed by a decline in $\beta_N$ during this second sub-period.

### 5.4.3 Panel-data estimation

We corroborate the preliminary impressions from the cross-sectional analysis by estimating the panel model (5.6), both for the periods 1963-1980 and 1980-1998, as well as for the most recent sub-period 1990-1998. This exercise allows us to boil down the sequence of point estimates into overall averages during the respective sub-periods. Moreover, the pooled estimation has higher power than the cross-sectional regressions which makes the test of no neighborhood bias ($\beta_N = 0$) more reliable.

Table 5.1: Spatial risk sharing model with spatial error autocorrelation and fixed effects, estimated using the estimator developed by Elhorst (2003)

| | **1963-1980** | | | **1980-1998** | | |
|---|---|---|---|---|---|---|
| | *Coeff.* | *t-stat* | *z-Prob.* | *Coeff.* | *t-stat* | *z-Prob.* |
| Own idiosyncratic output shock: $\Delta x$ ($\beta_K$) | 0.71 | (39.76) | (0.00) | 0.48 | (27.87) | (0.00) |
| Neighbor's idiosyncratic output shock: $[WB_t]\Delta x_t$ ($\beta_N$) | -0.02 | (-0.63) | (0.53) | 0.08 | (2.22) | (0.03) |
| Overall insurance: $\beta_K + \beta_N$ | 0.69 | | | 0.56 | | |
| Spatial autocorrelation coefficient ($\rho$) | 0.44 | (10.21) | (0.00) | 0.35 | (7.90) | (0.00) |
| log-likelihood | 2429.502 | | | 2706.78 | | |
| Number of observations | 816 | | | 912 | | |

| | **1990-1998** | | |
|---|---|---|---|
| | *Coeff.* | *t-stat* | *z-Prob.* |
| Own idiosyncratic output shock: $\Delta x$ ($\beta_K$) | 0.45 | (14.52) | (0.00) |
| Neighbor's idiosyncratic output shock: $[WB_t]\Delta x_t$ ($\beta_N$) | 0.23 | (3.53) | (0.00) |
| Overall insurance: $\beta_K + \beta_N$ | 0.68 | | |
| Spatial autocorrelation coefficient ($\rho$) | 0.19 | (2.68) | (0.00) |
| log-likelihood | 1314.75 | | |
| Number of observations | 432 | | |

The regression results of the pooled model (5.6) are displayed in Table 5.1. We estimated the model with the estimator for spatial panels with fixed effects and spatial error autocorrelation developed by Elhorst (2003).[19]

The first thing to note is that the spatial autocorrelation coefficient $\rho$ is statistically different from zero in all estimations. Therefore, the spatial panel estimator employed is indeed a more efficient estimator than simple OLS. Though, the point estimates of $\beta_K$ and $\beta_N$ reported in Table 5.1 are very similar to an OLS regression with fixed effects. A candidate interpretation of the nuisance spatial dependence in the error term is that it results from measurement problems such as the mismatch between the pattern of regional risk sharing and the boundaries of US federal states (see Magrini (2004) for a similar argument).

More important is that the results of the panel-data estimations confirm our previous examination of Figures 5.1 and 5.2. During the first sub-period, capital market risk sharing was rather scarce. The estimate of $\beta_K = 0.71$ implies that only about 30% of an own idiosyncratic output shock is smoothed via this channel. At the same time, the point estimate for $\beta_N = -0.02$ is not significantly different from zero, as we would expect from Figure 5.2.

Since we find the parameter $\beta_N$ to be insignificant, there is evidence that capital market linkages with neighboring states have not been more pronounced than linkages with other states during the first sub-period. Taken together, the coefficients $\beta_K$ and $\beta_N$ imply that an idiosyncratic output shock which hits the representative state is transmitted substantially to a change in the state's own income but output shocks to neighboring states do not affect the income of the home state significantly.

In order to quantify the overall amount of income insurance that is achieved we can add the coefficients $\beta_K$ and $\beta_N$ (see Table 5.1). This sum measures how strongly a state's idiosyncratic income changes if both, the home state and the neighbors are hit by idiosyncratic shocks. Or to put it differently, we can interpret the sum of $\beta_K$ and $\beta_N$ as the co-movement of state-level income with shocks that hit larger geographical areas. During 1963-1980 the influence of $\beta_N$ is negligible since the parameter is small and insignificant and one arrives at an overall amount of unsmoothed shocks of 0.69.

During the second sub-period 1980-1998 we find a different picture. As can be seen from the right-most columns in Table 5.1, the average amount of risk sharing of an own idiosyncratic output shock is substantially higher and corresponds to roughly 50 percent. As we could already infer from the graphical

[19] A MATLAB procedure for this estimator is freely downloadable from the website www.spatialeconometrics.com.

analysis before, also the neighborhood bias has increased during this period. The point estimate for $\beta_N$ is 0.08 and we can reject the hypothesis that the coefficient is 0.

In order to corroborate that the neighborhood bias has increased substantially over time we also estimate our panel model for the most recent period 1990-1998 only. This period may best reflect the influence of globalization on risk sharing and neighborhood bias.

From Table 5.1 (bottom) it can be seen that insurance against own idiosyncratic risk is highest during this recent period ($\beta_K = 0.45$). By sharp contrast, the co-movement of state-level income with neighbor's output has increased substantially. While the coefficient of the spatial lag of the idiosyncratic output shock was insignificant during the first period 1963-1980, it takes a value of $\beta_N = 0.23$ in recent years.

These findings indicate that we may have to qualify the overall increase in income insurance that is achieved during the second sub-period, and especially during more recent years. If we were to rely solely on a comparison of the $\beta_K$'s over time we would arrive at an impressing increase in capital market risk sharing from the first (1963-1980: $\beta_K = 0.71$) to the second sub-period (1980-1998: $\beta_K = 0.48$). If we account for spatial linkages among states, however, we find that the overall amount of income insurance measured by $48\% + 8\% = 56\%$ is still larger than the insurance achieved during the first period, but the increase is less pronounced than suggested by the $\beta_K$'s alone. This picture becomes even more pronounced during the period 1990-1998. Since the neighborhood bias has gained substantially in importance, the average federal state is insured only moderately against shocks that hit a larger geographical area. In fact, the sum of the $\beta$s during the most recent period (1990-1998: $\beta_K + \beta_N = 0.68$ (!)) is found to be the same as during 1963-1980.

However, this preliminary conclusion neglects one important aspect, namely to account for the variance of neighbor's idiosyncratic output risk relative to one's own output risk. To illustrate this point we may consider two extreme cases. If there is no diversification at all, agents hold claims to the output produced in their own state only and consequently we would find $\beta_K = 1$ and $\beta_N = 0$. The other extreme case is that agents hold claims to output in neighboring states solely. In this scenario it holds that $\beta_K = 0$ and $\beta_N = 1$.

Both extreme scenarios have different consequences for the overall effectiveness of income insurance. In the second scenario of a complete neighborhood bias one's income will fluctuate *less* than in the first scenario of a complete home bias 'at home'. The reason is that the output fluctuation of neighbors is smaller than the output variability at home. In other words, a disproportionate high engagement in neighbor's output stream reduces the variability of income at home because a limited amount of diversification takes place. In fact, if all states had independent idiosyncratic risk, investing one more dollar in the output stream of neighboring states (equally split) would reduce the fluctuation of income at home by a factor $1/N_k$, where $N_k$ is the number of neighbors.

In order to account for this effect we scale the coefficient associated with the neighborhood bias, $\beta_N$, by the ratio of the standard deviations of neighbor's and one's own output risk. Specifically, we transform the point estimate of $\beta_N$ as

$$\tilde{\beta}_N = \frac{\beta_N}{std\,(\Delta x_t)} \cdot std\,([WB_t]\Delta x_t)\,.$$

We report the standardized estimates of $\tilde{\beta}_N$ for the three sub-periods in the first row of Table 5.2. As expected, our previous conclusion concerning the destabilizing effect of the neighborhood bias has to be qualified. Once we account for the smaller variance of neighbor's output relative to one's own output we arrive at smaller estimates for $\tilde{\beta}_N$. Quite symmetrically, the estimates decline by roughly one half. Therefore, we note that our estimates reported in Table 5.1 cast a too damning light on the neighborhood bias.

More important is, however, that we find a similar development of the neighborhood bias over time even if we account for the potential gain in variance reduction in one's own income. Specifically, the standardized neighborhood bias is found to be unimportant during 1963-1980 but it is becoming more pronounced during 1980-1998. Especially during the most recent period 1990-1998, the magnitude of the (standardized) $\tilde{\beta}_N$ coefficient is clearly significant also in economic terms.

The second row of Table 5.2 displays the overall degree of income insurance which is achieved once we account for the smaller variance in neighbor's output fluctuation, calculated as $\beta_K + \tilde{\beta}_N$. The numbers provide evidence that the amount of risk sharing during the second sub-period is indeed larger than during the first one. However, the increase is still less pronounced than suggested by a comparison of the $\beta_K$'s alone. These estimates are replicated in the last row of Table 5.2 for ease of comparison.

The overall conclusion suggested by our spatial risk sharing model can be summarized as follows. As also documented by Kalemli-Ozcan, Sørensen, and Yosha (2004), income fluctuations have indeed become substantially decoupled from fluctuations in one's own output. At the same time, state-level income has become more dependent on neighbor's output fluctuation than in the past.

Table 5.2: Standardized estimates of the neighborhood bias

| | 1963-1980 | 1980-1998 | 1990-1998 |
|---|---|---|---|
| $\tilde{\beta}_N = \frac{\beta_N}{std(\Delta x_t)} \cdot std\left([WB_t]\Delta x_t\right)$ | -0.01 | 0.04 | 0.12 |
| Overall insurance: $\beta_K + \tilde{\beta}_N$ | 0.70 | 0.52 | 0.57 |
| Own idiosyncratic output shock: $\beta_K$ [taken from Table 5.1] | 0.71 | 0.48 | 0.45 |

The net effect of both developments is a more moderate increase in income insurance provided by capital markets than documented in previous studies which do not take the neighborhood bias into account.

## 5.5 Accounting for commuter flows

Having shown that the neighborhood bias in factor income flows has become more pronounced over time, a next step in the analysis is to examine which economic factors drive the development of the neighborhood bias. As we have discussed in Sections 1 and 2, the neighborhood bias may be driven by capital income flows, but also by labor income flows. Both income components are reflected in the wedge between GSP and income.

In order to assess the relative importance of both factors we extend the analysis to include commuter flows across state borders. The role of commuter flows has been emphasized in a different area of economic research, namely that of growth and convergence. A prevalent finding in this literature is that changes in commuter patterns represents an important source of spatial adjustment (see Magrini, 2004). Therefore, it is important to examine how much of the neighborhood bias may be explained by commuter flows.

If workers commute from their place of residence to their place of work in another federal state, their output is attributed to the GSP of the neighboring state, while their income is measured at their state of residence. Idiosyncratic output shocks that hit neighboring states may then be transmitted to the home state's income because workers, who commute to their place of work, take their output produced in other states with them (in the form of income).

To the best of our knowledge, consecutive time-series data on commuter flows across US federal states is not available. The only data which is available are special tabulations from the decennial Censuses of 1960, 1970, 1980, 1990, and 2000 which show the commuting flows between counties.[20]

We aggregate the county data for 1990 and 2000 to the federal state level and compute the flow of commuters into and out of each federal state at both points in time. Moreover, we compute the net inflow of commuters into each state. All numbers are normalized by the state's employment in order to obtain commuter rates.

For instance, a positive value of the net commuter rate indicates that more workers commute from neighboring states into that state than in the opposite direction. In other words, a positive net commuter rate indicates that employment measured at the workplace is larger than employment measured at the place of residence. To illustrate the overall commuting patterns among US federal states Figure 5.3 presents a map of net commuter rates for 1990 and 2000.

We apply two strategies to test whether commuter flows are a candidate explanation for the high values of $\beta_N$ found in more recent years. Firstly, we exclude those states from the analysis which are characterized by either very high or very low net commuter rates. This exercise prevents those states from dominating our estimate for $\beta_N$. Secondly, we parametrize $\beta_N$ as a function of commuter flows.

Concerning the first strategy, we use an ad-hoc rule and exclude those states from the analysis which fall outside the 10 to 90 percent percentile of net commuter rates. We note that our results are robust to using a different threshold. When we use this threshold the number of states included in the analysis declines substantially from 48 to 38.

To save on space, we only report the estimation results for those periods in which the coefficient $\beta_N$ was found to be significant, i.e. for 1980-1998 and the most recent period 1990-1998. From Table 5.3 it can be seen that our previous point estimates for $\beta_N$ do not change substantially. In particular, we obtain a large estimate for $\beta_N$ during the period 1990-1998 which is close to the estimate obtained for the complete sample of states. Therefore, states with very high inflows or outflows of commuters do not drive our previous finding of a sizeable neighborhood bias in factor income flows.

[20] The data for 1990 and 2000 can be downloaded from `http://www.census.gov/population/www/cen2000/commuting.html`. We do not have access to data from earlier years. Data for 1960-1980 will be considered in a later version of this paper.

Figure 5.3: Net commuter rates across US federal states, 1990 (top) and 2000 (bottom)

Table 5.3: Exclude federal states with intensive commuter flows

| | **1980-1998** | | | **1990-1998** | | |
|---|---|---|---|---|---|---|
| | *Coeff.* | *t-stat* | *z-Prob.* | *Coeff.* | *t-stat* | *z-Prob.* |
| Own idiosyncratic output shock: $\Delta x$ ($\beta_K$) | 0.49 | (28.61) | 0.00 | 0.40 | (12.08) | 0.00 |
| Neighbor's idiosyncratic output shock: $[WB_t]\Delta x_t$ ($\beta_N$) | 0.07 | (2.08) | 0.04 | 0.21 | (3.32) | 0.00 |
| Overall insurance: $\beta_K + \beta_N$ | 0.56 | | | 0.61 | | |
| Spatial autocorrelation coefficient ($\rho$) | 0.35 | (7.99) | 0.00 | 0.14 | (1.98) | 0.05 |
| log-likelihood | 2192.07 | | | 1051.76 | | |
| Number of observations | 722 | | | 342 | | |
| Number of states | 38 | | | 38 | | |
| Number of years | 19 | | | 9 | | |

We provide further evidence by analyzing directly whether states that have high commuter flows are more or less successful in decoupling their incomes from the output fluctuation in neighboring states. This means that we relax the assumption that $\beta_N$ is the same for all federal states. To capture the impact of commuter flows on our measure of neighborhood bias, we postulate that $\beta_N$ may vary across states and is given by

$$\beta_{N,k} = \kappa' (c_{k,t} - \bar{c}_t) \tag{5.7}$$

where $c_{k,t}$ is a vector of data on commuter flows and $\bar{c}_t$ is the vector of cross-sectional means of $c_{k,t}$. The associated parameter vector is denoted as $\kappa$. Before we discuss how to interpret (5.7) we note that the vector $c_{k,t}$ could contain different measures of commuter flows. For instance, $c_{k,t}$ may include commuter flows (rates) into and out of each federal state. Alternatively, we could focus on the net rate of commuter flows. Lastly, we could emphasize the role of gross commuter flows rather than net flows by adding commuter flows in both directions (see below).

Each of these possibilities to parametrize $\beta_{N,k}$ has pros and cons and we have no strong prior which specification is preferable. To set the scene, we start with a general specification and include both, commuting into and commuting out of a federal state into the vector $c_{k,t}$. Thereafter, we turn to an alternative specification which emphasizes the effect of gross flows. Finally, we consider commuting *out* of a federal state only.

For our first parametrization we define commuter rates as

$$z_{k,t}^{in} = \frac{Z_{k,t}^{in}}{E_{k,t}} \quad \text{and} \quad z_{k,t}^{out} = \frac{Z_{k,t}^{out}}{E_{k,t}},$$

where $Z_{k,t}^{in}$ measures commuter flows into a state and $Z_{k,t}^{out}$ measures commuting out of a state. Both numbers are normalized by total employment $E_{k,t}$, so that the lower-case variables $z$ measure commuter rates.

Then, we define the parametrization of $\beta_{N,k}$ as

$$\beta_{N,k} = \bar{\beta}_N + \kappa_1(z_{k,t}^{in} - \bar{z}_t^{in}) + \kappa_2(z_{k,t}^{out} - \bar{z}_t^{out}). \tag{5.8}$$

We note that we do not have a consecutive time-series on commuter flows. Therefore, we stacked commuter flows in 1990 and 2000 so that the period 1980-1990 is matched with commuter flows in 1990 and the remaining years between 1990-1998 are matched with commuting data in 2000. Although this crude procedure is far from being satisfactory, it seems the best we can do at the moment due to the aforementioned data limitations. We hope that this exercise provides us at least with an idea of how strongly differences in commuter flows affect the estimate for $\beta_N$.

We substract the vectors of cross-sectional means (indicated with an upper-bar, see equation (5.8)) from each commuter rate. This allows us to interpret the coefficient $\bar{\beta}_N$ as the cross-sectional average of $\beta_{N,k}$. Plugging the relation (5.8) into (5.6) then yields a panel regression from which the coefficients $\kappa_1$ and $\kappa_2$ can be estimated.

The estimation results are reported in Table 5.4 (top). The most important finding is that the commuter variables are not statistically significant during both sub-periods. This finding implies that a federal state which is characterized by above-average commuter flows has a similar degree of neighborhood bias than a state which is characterized by an average amount of commuter flows.

As a robustness test we also estimated the panel model without fixed-effects.

Table 5.4: Impact of commuter flows on the neighborhood bias, Part I

**Parametrization I:** $\beta_{N,k} = \bar{\beta}_N + \kappa_1(z_{k,t}^{in} - \bar{z}_t^{in}) + \kappa_2(z_{k,t}^{out} - \bar{z}_t^{out})$

| | 1980-1998 | | | 1990-1998 | | |
|---|---|---|---|---|---|---|
| | *Coeff.* | *t-stat* | *z-Prob.* | *Coeff.* | *t-stat* | *z-Prob.* |
| Own idiosyncratic output shock: $\beta_K$ | 0.49 | (27.94) | 0.00 | 0.44 | (14.13) | 0.00 |
| Neighbor's idiosyncratic output shock: $\bar{\beta}_N$ | 0.09 | (2.56) | 0.01 | 0.26 | (3.89) | 0.00 |
| Commuter rate (in): $\kappa_1$ | 0.49 | (0.27) | 0.78 | 2.46 | (0.67) | 0.50 |
| Commuter rate (out): $\kappa_2$ | 1.63 | (1.48) | 0.14 | 1.77 | (0.75) | 0.45 |
| Spatial autocorrelation coefficient $\rho$ | 0.35 | 7.99 | 0.00 | 0.19 | (2.65) | 0.01 |

**Parametrization II:** $\beta_{N,k} = \beta_N + \kappa_3 z_{k,t}^{gross}, \quad z_{k,t}^{gross} = \left(Z_{k,t}^{in} + Z_{k,t}^{out}\right)/E_{k,t}$

| | 1980-1998 | | | 1990-1998 | | |
|---|---|---|---|---|---|---|
| | *Coeff.* | *t-stat* | *z-Prob.* | *Coeff.* | *t-stat* | *z-Prob.* |
| Own idiosyncratic output shock: $\beta_K$ | 0.49 | (27.98) | 0.00 | 0.44 | (14.19) | 0.00 |
| Neighbor's idiosyncratic output shock: $\beta_N$ | -0.01 | (-0.13) | 0.90 | 0.08 | (0.78) | 0.44 |
| Gross commuter rate: $\kappa_3$ | 1.25 | (2.47) | 0.01 | 2.03 | (1.99) | 0.05 |
| Spatial autocorrelation coefficient: $\rho$ | 0.35 | (7.92) | 0.00 | 0.19 | (2.65) | 0.01 |

This exercise illustrates if potential cross-sectional variation in $\beta_{N,k}$ through differences in commuter flows becomes significant once we omit the fixed-effects which also pick up heterogeneity across states. We do not report detailed results of this exercise because none of the $\kappa$ coefficients becomes significant even if fixed-effects are omitted.

Although these findings are important on their own, we should also consider alternative specifications which we believe have a more direct economic interpretation in our setting. The parametrization according to (5.8) illustrates whether *deviations* from *average* levels of commuter flows have an influence on the neighborhood parameter $\beta_N$ and we found that this is not the case. It is also of importance, however, to examine whether the magnitude of $\beta_N$ changes substantially once a (fictitious) federal state is *completely* isolated from other states in terms of commuting. In order to test whether the neighborhood bias in factor income flows vanishes once commuter flows are (artificially) set to zero, we consider the following parametrization of $\beta_{N,k}$:

$$\beta_{N,k} = \beta_N + \kappa_3 z_{k,t}^{gross}, \tag{5.9}$$

where the regressor $z_{k,t}^{gross}$ measures the sum of gross commuter flows (rather than the net flow). We calculate $z_{k,t}^{gross}$ as

$$z_{k,t}^{gross} = \frac{Z_{k,t}^{in} + Z_{k,t}^{out}}{E_{k,t}}.$$

In this formula, $Z_{k,t}^{in}$ measures commuter flows into a state, $Z_{k,t}^{out}$ measures commuter flows out of a state, and $E_{k,t}$ is total employment of state $k$ at time $t$. Different from the previous parametrization we do not subtract the cross-sectional averages of $z_{k,t}^{gross}$. This allows us to interpret the coefficient $\beta_N$ in equation (5.9) as the amount of neighborhood bias if there were no commuter flows (at all).

Table 5.4 (bottom) reports the results obtained with this specification. It can be seen that the results change substantially. The point estimates for $\beta_N$ become insignificant while the interaction term with the commuter variable becomes significant in both periods. These estimates suggest that if there were no commuter flows, there would also be no neighborhood bias in factor income flows.

However, it might be that the $\beta_N$ coefficient is imprecisely estimated due to problems of multi-collinearity. In any case, it is important to note that the point estimate of $\beta_N$ during the period 1990-1998 declines substantially from

0.23 (see Table 5.1) to 0.08 (see Table 5.4).

In order to illustrate the quantitative effects associated with the parameter of the interaction term, $\kappa_3$, we consider a one standard-deviation increase in gross commuter flows as an example. If the gross commuter rate increases by one standard deviation this induces an increase in $\beta_N$ of 0.14.

Finally, we consider a parametrization of $\beta_{N,k}$ which only takes into account commuter flows *out* of a federal state. This specification should illustrate most clearly whether the apparent neighborhood bias in factor income flows essentially reflects commuters income which crosses state borders. If workers commute from their place of residence to their place of work in another federal state, their output is attributed to the GSP of the neighboring state, while their income is measured at their state of residence. Hence, idiosyncratic output fluctuations in neighboring states may be transmitted to the home state's income because workers commuting to their place of work take their output produced in other states with them.

To test for this effect (whilst ignoring the effect of commuting into a federal state) we parametrize the parameter associated with the neighborhood bias as

$$\beta_{N,k} = \beta_N + \kappa_4 z_{k,t}^{out}, \tag{5.10}$$

where $z_{k,t}^{out}$ measures the commuter rate out of a state. The results of the estimation are displayed in Table 5.5.

Again, we find strong evidence that the neighborhood bias is far from being a phenomenon unique to the capital market. In both sub-periods the interaction term of neighbor's output shock with the commuter rate is statistically significant, though only at the 10% level during 1990-1998. The parameter associated with the neighborhood bias itself becomes insignificant, most likely due to problems of multi-collinearity.[21] Even more important is that its point estimate declines substantially from 0.23 (see Table 5.1) to 0.11 (see Table 5.5). This finding provides further evidence that it are commuter flows which explain a large fraction of the neighborhood bias in factor income flows.

If we look at the quantitative effects, we find that a one standard-deviation increase in the commuter rate out of a state increases the transmission of neighbor's output shocks to a state's idiosyncratic income by 0.19. In other words, if no workers were commuting into neighboring states at all, the neighborhood bias would decline to a magnitude of 0.11. A one standard-deviation increase in

[21] The correlation between neighbor's idiosyncratic output shock $[WB_t]\Delta x_t$ and the interaction term is of magnitude 0.8.

Table 5.5: Impact of commuter flows on the neighborhood bias, Part II

**Parametrization III:** $\beta_{N,k} = \beta_N + \kappa_4 z_{k,t}^{out}$, $z_{k,t}^{out} = \frac{Z_{k,t}^{out}}{E_{k,t}}$

| | 1980-1998 | | | 1990-1998 | | |
|---|---|---|---|---|---|---|
| | *Coeff.* | *t-stat* | *z-Prob.* | *Coeff.* | *t-stat* | *z-Prob.* |
| Own idiosyncratic output shock: $\beta_K$ | 0.49 | (27.96) | 0.00 | 0.44 | (14.28) | 0.00 |
| Neighbor's idiosyncratic output shock: $\beta_N$ | 0.01 | (0.13) | 0.89 | 0.11 | (1.19) | 0.23 |
| Commuter rate (out): $\kappa_4$ | 1.89 | (2.47) | 0.01 | 2.94 | (1.87) | 0.06 |
| Spatial autocorrelation coefficient: $\rho$ | 0.35 | (7.90) | 0.00 | 0.19 | (2.60) | 0.01 |

the commuter rate would increase the neighborhood bias by further 0.19 units.

## 5.6 Extensions for future research

In this paper we have established a first link between the literatures on spatial econometrics and risk sharing. We are convinced that our study suggests a number of promising directions for further inquiry.

One extension is to measure risk sharing among larger geographical areas than at the state level. Such experiment can illustrate whether the apparent neighborhood bias in factor income flows vanishes once state-level data are aggregated. We would expect that the amount of risk sharing among larger geographical areas is smaller than suggested by previous studies which used state-level data and did not account for the neighborhood bias in factor income flows.

Secondly, it appears promising to take our spatial approach to the international economy. We suppose that the neighborhood bias may turn out to be important, given the vast distances separating investors from potential investments in the global setting. At the same time, commuter flows between states are expected to play a minor role for the international economy.

For the international economy, several studies have documented a gradual removal of country portfolio home bias in recent years. For instance, Lane and Milesi-Ferretti (2001, 2003) document a dramatic increase in international cross-holdings of financial assets. Since data on international asset holdings is available we could use this data to test how well our spatial model picks up the development of local biases in investment portfolios over time.

Another step in the analysis might be to re-consider the approach taken by Artis and Hoffmann (2005). While our model relied solely on output and income data which have been rendered stationary through first-differencing, this study demonstrates how to use the information implicit in the levels of relative *consumption* and output. The advantage of the level specification is that it allows one to pick up longer-term trends in the extent of consumption risk sharing that remain blurred in the first-differenced specification for capital market risk sharing. Some pre-testing makes us confident that spatial effects are highly relevant in the levels model. On the side of the econometric analysis, a spatial risk sharing analysis in levels needs to combine cointegration and spatial econometric techniques.

## 5.7 Conclusion

Previous risk sharing studies have analyzed how well income is insured against idiosyncratic fluctuations in one's own output. From micro-based studies we know, however, that regional asset portfolios are characterized by a preference for geographically proximate investments which is related to distance and information asymmetries among regions. This implies that output fluctuations in neighboring states may also exert a destabilizing effect on state-level incomes. We have referred to this phenomenon as a 'neighborhood bias'.

The question of this paper has been how strongly a potential neighborhood bias influences the overall amount of income insurance that is achieved among US federal states. Or to put it differently, we have examined whether output fluctuations in neighboring states also constitute risk factors which are transmitted to the home state's idiosyncratic income via factor income flows. This paper is the first one that puts local biases in factor income flows into a regional perspective.

Similar to previous studies, we found that insurance against own idiosyncratic shocks has increased substantially over time. This means that state-level income has become more and more buffered against region-specific shocks to GSP.[22] At the same time, however, factor income flows have become substantially biased towards neighboring states in recent years. This means that factor income flows between states and their neighbors are disproportionately high in comparison to a portfolio which only takes into account the fraction of a state's output. As a consequence, state-level income co-moves not only with own idiosyncratic output fluctuations, but also with output growth of neighboring states. Therefore, our study suggests that the overall amount of income insurance is more limited than reported in previous studies which did not take the neighborhood bias into account.

In a second step, we have examined which economic factors drive the neighborhood bias in factor income flows. There are two candidate explanations for the neighborhood bias. Firstly, local biases in capital income flows caused by local biases in portfolio holdings and secondly, commuter flows across state-borders.

We incorporated commuter flows into the analysis in order to shed light on the relative importance of both factors. We found that a fictitious federal state which is completely isolated from other states in terms of commuting is not subject to a neighborhood bias in factor income flows—at least the statistical significance of the neighborhood bias vanishes for this state. Thus, the apparent neighborhood bias in factor income flows does not primarily reflect a preference for geographically proximate investments, but mainly the effect of commuting linkages among states. We believe that this result is of utmost importance since it also suggests that risk sharing itself is not an issue of capital markets solely.

These results were derived by extending the standard risk sharing model to a spatial model. Besides the empirical results of our estimations, a further contribution of our paper is to have established a first link between the risk sharing and the spatial econometrics literature. These fields have been unrelated so far.

[22] Further smoothing of income can be achieved through federal taxes and transfers and by borrowing and lending at the credit market. These channels were not in the focus of this paper.

# Chapter 6

# Concluding Remarks

In this thesis I have presented four self-contained essays on empirical and policy issues related to economic convergence and risk sharing. My essays contribute to the emerging literature on 'Intranational Macroeconomics' (see Hess and van Wincoop, 2000), which aims at complementing and extending international studies by examining the high degree of goods and asset market integration within a domestic setting. The main results of my papers can be summarized as follows.

In **Chapter 2** I have provided evidence for conditional convergence in regional unemployment rates in West Germany. The equilibrium distribution of regional unemployment rates was found to be subject to a permanent shift which occurred after the second oil crisis. The finding of structural breaks and quick adjustment to equilibrium levels implies that small policy interventions are unlikely to be effective in reducing the dispersion of unemployment rates. Rather, policy intervention needs to take the form of a substantial intervention.

**Chapter 3** moved the focus to an analysis of regional convergence in reunified Germany. By examining the density functions of GDP per worker I have illustrated that East German regions have caught up substantially in the past decade. In the long-run, however, my finding of a bi-modal ergodic distribution provides some discouraging evidence that regional polarization in production is likely to persist if past distribution dynamics continue operating unchanged in the future.

Yet, one important insight from the theory of aggregate risk sharing is that disparities in production do not necessarily induce disparities in welfare. The analysis presented in **Chapter 4** has shown that disparities in levels of regional output are reduced by private factor income flows and public interregional transfers. While private factor income flows provide substantial insurance against idiosyncratic output risk, fiscal transfers are found to contribute significantly to reducing level disparities in household incomes.

Finally, **Chapter 5** examined regional risk sharing among US federal states. One central result of the analysis is that the increasing amount of insurance against own idiosyncratic output fluctuations over time is accompanied by an increasing dependence on output fluctuations in geographically proximate states. A large fraction of this dependence on neighbors output variability may be explained by better commuting possibilities across state borders.

From a methodological point of view, the central contribution of my thesis is a cross-fertilization between the modern literature on growth econometrics and the macroeconomic literature on aggregate risk sharing. The transfer of insights from one field of macroeconomic research to the other focused on a transfer of analytical techniques, rather than that it attempted to shed light on the economic relationships between these topics. In fact, this would have been necessarily beyond the scope of the individual papers. However, these concluding remarks allow me to draw a bow from one field of research to the other.

Typically, the literature on risk sharing is motivated by the belief that substantial welfare gains can be achieved by risk sharing. As summarized by van Wincoop (1994) and Athanasoulis and van Wincoop (2000, 2001), the welfare gains from risk sharing depend on four factors: (i) the risk-free interest rate, (ii) the risk-adjusted growth rate, (iii) the rate of relative risk aversion, and (iv) uncertainty about the endowment.

The last of these factors is of particular importance and is in fact closely related to the question of economic convergence. In other words, one connection between the fields of risk sharing and convergence is the uncertainty about the endowment.

Obviously, the uncertainty about the endowment depends on the specific process for the endowment. Usually, studies on risk sharing assume that the relative output process displays a high degree of persistency. In fact, the variance decomposition method suggested by Asdrubali, Sørensen, and Yosha (1996)—which has become the workhorse for most macroeconomic studies on inter- and intranational risk sharing—assumes that relative output follows a unit-root process and is hence unpredictable. The higher the persistency of output is, the higher are possible welfare gains from sharing output risk. By contrast, a low degree of persistency in the output process corresponds to shocks being only transitory, short-lived, and predominantly small in magnitude.

As illustrated in Chapter 2, also the notion of economic convergence is related to uncertainty about the endowment, which is again reflected by the time-series properties of variables employed. As such, time-series tests of convergence judge convergence by examining how closely macroeconomic time-series can be approximated by unit-root processes. If relative output follows a unit-root process than there is no convergence.

These considerations reveal that the risk sharing literature builds implicitly upon empirical findings which have been established by the convergence literature, namely the prevalent property of macroeconomic time-series to display a high degree of persistency. Or to put it differently, there is ample scope for risk sharing if convergence occurs only slowly over time.

Risk sharing also implies that convergence in income (or consumption) should occur faster than convergence in output. The reason is that convergence in income can be achieved by flows in factor income, while convergence in output requires a flow of productive factors themselves. In other words, the theory of macroeconomic risk sharing suggests that convergence in income can be achieved by trade in *financial* assets, while convergence in output requires trade in *real* assets.

# Bibliography


Abreu, M. (2005). 'A Meta-analysis of $\beta$-convergence: The Legendary 2%.' *Journal of Economic Surveys* 19: 389-420.

Aghion, P. and Howitt P. W. (eds.) (2005). *Handbook of Economic Growth.* Amsterdam, North Holland.

Ahearne, A. G., Griever, W. L. and Warnock, F. E. (2004). 'Information Costs and Home Bias: An analysis of U.S. Holdings of Foreign Equities.' *Journal of International Economics* 62: 313-336.

Amable, B., Henry, J., Lordon, F. and Topol, R. (1991). 'Strong Hysteresis: An Application to Foreign Trade.' *OFCE Working Paper/Document de travail no. 9103*, Observatoire Francais des Conjonctures Economiques, Paris.

Amable, B., Henry, J., Lordon, F. and Topol, R. (1994). 'Strong Hysteresis versus Zero-Root Dynamics.' *Economics Letters* 44: 43-47.

Amable, B., Henry, J., Lordon, F. and Topol, R. (2005). 'Complex Remanence vs. Simple Persistence: Are Hysteresis and Unit Root Processes Obervationally Equivalent?' *mimeo.*

Anselin, L., Florax, R. J. G. M. and Rey, S. J. (eds.) (2004). *Advances in Spatial Econometrics.* Springer, Berlin.

Armstrong, H. and Taylor, J. (2000). *Regional Economics and Policy*, 3rd. edn, Blackwell.

Andrade, E., Laurini, M., Madalozzo, R. and Valls Pereira, P. L. (2005). 'Convergence clubs among Brazilian municipalities.' *Economics Letters* 83: 179-184.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models.* Kluwer Academic Publishers, Dorddrecht.

Artis, M. J. and Hoffmann, M. (2005). 'The Home Bias and Capital Income Flows between Countries and Regions.' *mimeo*, University of Dortmund.

Asdrubali, P., Sørensen, B. E. and Yosha, O. (1996). 'Channels of interstate risk sharing: United States 1963-90.' *Quarterly Journal of Economics* 111: 1081-1110.

Asdrubali, P. and Kim, S. (2004). 'Dynamic risksharing in the United States and Europe.' *Journal of Monetary Economics* 51: 809-836.

Asdrubali, P. and Kim, S. (2005). 'Incomplete Intertemporal Consumption Smoothing and Incomplete Risk Sharing.' *mimeo.*

Athanasoulis, S. G. and van Wincoop, E. (2000). 'Growth uncertainty and risksharing.' *Journal of Monetary Economics* 45: 477-505.

Athanasoulis, S. G. and van Wincoop, E. (2001). 'Risk sharing within the United States: What do financial markets and fiscal federalism accomplish?' *Review of Economics and Statistics* 83: 688-698.

Atkeson, A. and Bayoumi, P. R. (1993). 'Do Private Capital Markets Insure Regional Risks? Evidence from the United States and Europe.' *Open Economics Review* 4: 303-324.

Azariadis, C. and Drazen, A. (1990). 'Threshold Externalities in Economic Development.' *Quarterly Journal of Economics* 105: 501-526.

Baltagi, B. H. (2001). *Econometric Analysis of Panel Data*, John Wiley & Sons.

Balz, C. (1999). 'Hysteresis auf europäischen Arbeitsmärkten. Neue empirische Ergebnisse auf der Basis multivariater Einheitswurzeltests.' *Konjunkturpolitik* 45: 221-239.

Bandyopadhyay, S. (2002). 'Convergence Club Empirics: Some Dynamics and Explanations of Unequal Economic Growth across Indian states.' *DARP Discussion Paper* No. 69., STICERD, London School of Economics.

Bandyopadhyay, S. (2004). 'Twin Peaks: Distribution Dynamics of Economic Growth across Indian States.' In: Shorrocks, A. and van der Hoeven, R. (eds.), *Growth, Inequality and Poverty: Prospects for Pro-Poor Growth.* Oxford University Press.

Barrell, R. and te Velde, D. W. (2000). 'Catching-up of East German labor Productivity in the 1990s.' *German Economic Review* 1: 271-297.

Barro, R. J. (1991a). 'Economic Growth in a Cross Section of Countries.' *Quarterly Journal of Economics* 106: 407-443.

Barro, R. J. and Sala-i-Martin, X. (1991b). 'Convergence across States and Regions.' *Brooking Papers on Economic Activity* 1: 107-182.

Barro, R. J. and Sala-i-Martin, X. (1992). 'Convergence.' *Journal of Political Economy* 100: 223-251.

Barro, R. J., Mankiw, N. G. and Sala-i-Martin, X. (1995). 'Capital Mobility in Neoclassical Models of Growth.' *American Economic Review* 85: 103-115.

Baxter, M. and Crucini, M. (1995). 'Business Cycles and the Asset Structure of Foreign Trade.' *International Economic Review* 36: 821-854.

Bayer, C. and Jüßen, F. (2006). 'Convergence in West German Regional Unemployment Rates.' Forthcoming in *German Economic Review*.

Becker, S. and Hoffmann, M. (2006). 'Intra- and International Risk-Sharing in the Short Run and the Long Run.' *European Economic Review* 50: 777-806.

Belke, A. (1996). 'Testing for Unit Roots in West German and U.S. Unemployment Rates: Do 'Great Crashes' Cause Trend Breaks?' *Konjunkturpolitik* 42: 327-360.

Belke, A. and Göcke, M. (1996). 'Cointegration and Structural Breaks in German Employment, An Error Correction Interpretation.' *Jahrbücher für Nationalökonomie und Statistik* 216: 129-152.

Belke, A. and Göcke, M. (2005). 'Real Options Effects on Employment: Does Exchange Rate Uncertainty Matter for Aggregation?' *German Economic Review* 6: 185-203.

Bernard, A. and Durlauf, S. (1995). 'Convergence in international output.' *Journal of Applied Econometrics* 10: 97-108.

Bernard, A. and Durlauf, S. (1996). 'Interpreting tests of the convergence hypothesis.' *Journal of Econometrics* 71: 161-73.

Bianchi, M. (1997). 'Testing for convergence: evidence from non-parametric multimodality tests.' *Journal of Applied Econometrics* 12: 393-409.

Blanchard, O. J. and Katz, L. (1992). 'Regional Evolutions.' *Brookings Papers on Economic Activity* 1: 1-75.

Blanchard, O. J. and Summers, L. H. (1989). 'Hysteresis and the European unemployment problem.' *NBER Macroeconomics Annual 1986* (ed. Fischer, S.), MIT Press, Cambridge (MA)..

Bliss, C. (1999). 'Galton's Fallacy and Economic Convergence.' *Oxford Economic Papers* 51: 4-14.

Bliss, C. (2000). 'Galton's Fallacy and Economic Convergence: A Reply to Cannon and Duck.' *Oxford Economic Papers* 52: 420-422.

Bode, E. and Rey, S. (2006). 'Introduction to the special issue "The Spatial Dimension of Economic Growth and Convergence"'. Forthcoming in *Papers in Regional Science.*

Bohl, M. T. (1998). 'Konvergenz westdeutscher Regionen? Neue empirische Ergebnisse auf der Basis von Panel-Einheitswurzeltests.' *Konjunkturpolitik* 44: 82-99.

Bond, S., Hoeffler, H. and Temple, J. (2001). 'GMM Estimation of Empirical Growth Models.' *CEPR Discussion Paper* No. 3048.

Breitung, J. and Meyer, W. (1994). 'Testing for Unit Roots in Panel Data: Are wages on different bargaining levels cointegrated?' *Applied Economics* 26: 353-361.

Breitung, J. (2000). 'The Local Power of Some Unit Root Tests for Panel Data.' In: Baltagi, B. (ed.), *Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, Advances in Econometrics, Vol. 15, JAI, Amsterdam: 161-178.

Brennan, M. and Cao, H. (1997). 'International Portfolio Investment Flows.' *Journal of Finance* 52: 1851-1880.

Buettner, T. (2002). 'Fiscal federalism and interstate risk sharing: empirical evidence from Germany'. *Economics Letters* 74: 195-202.

Bulli, S. (2001). 'Distribution Dynamics and Cross-Country Convergence: A New Approach.' *Scottish Journal of Political Economy* 48: 226-243.

Burda, M. and Funke, M. (1995). 'Eastern Germany: Can't We Be More Optimistic?' *IFO Studien* 41: 327-345.

Camarero, M. and Tamarit, C. (2004). 'Hysteresis vs. natural rate of unemployment: new evidence for OECD countries.' *Economics Letters* 84: 413-417.

Canova, F. and Ravn, M. (1996). 'International Consumption Risk Sharing.' *International Economic Review* 37: 573-601.

Cannon, E. and Duck, N. (2000). 'Galton's Fallacy and Economic Convergence.' *Oxford Economic Papers* 53: 415-419.

Carlino, G. and Mills, L. (1993). 'Are US regional incomes converging?' *Journal of Monetary Economics* 32: 335-346.

Carlino, G. and Mills, L. (1996a). 'Testing Neoclassical Convergence in Regional Incomes and Earnings.' *Regional Science and Urban Economics* 26: 565-590.

Carlino, G. and Mills, L. (1996b). 'Convergence and the U.S. States: a Time-Series Analysis.' *Journal of Regional Science* 36: 587-616.

Caselli, F., Esquivel, G. and Lefort, F. (1996). 'Reopening the Convergence Debate: A New Look at Cross-country Growth Empirics.' *Journal of Economic Growth* 1: 363-389.

Cass, D. (1965). 'Optimum Growth in an Aggregative Model of Capital Accumulation.' *Review of Economic Studies* 32: 233-240.

Choi, I. (2001). 'Unit root tests for panel data.' *Journal of International Money and Finance* 20: 249-272.

Cochrane, J. H. (1991). 'A simple test of consumption insurance.' *Journal of Political Economy* 99: 957-976.

Cooper, I. and Kaplanis, E. (1994). 'Home bias in equity portfolios, inflation hedging, and international capital market equilibrium.' *Review of Financial Studies* 7: 45-60.

Coval, J. D. and Moskowitz, T. J. (1999). 'Home bias at home: Local equity preference in domestic portfolios.' *Journal of Finance* 54: 2045-2074.

Coval, J. D. (2003). 'International capital flows when investors have local information.' *Harvard Business School Working Paper 04-026.*

Cross, R. (1994). 'The Macroeconomic Consequences of Discontinuous Adjustment: Selective Memory of Non-Dominated Extrema.' *Scottish Journal of Political Economy* 41: 212-221.

Crucini, M. J. (1999). 'On international and national dimensions of risk sharing.' *Review of Economics and Statistics* 81: 73-84.

Crucini, M. J. and Hess, G. D. (2000). 'International and intranational risk sharing.' In: Hess, G. D. and van Wincoop, E. (eds.), *Intranational Macroeconomics.* Cambridge University Press, Cambridge.

Decressin, J. and Fatas, A. (1995). 'Regional Labor Market Dynamics in Europe.' *European Economic Review* 39: 1627-1655.

Del Negro, M. (2002). 'Asymmetric shocks among U.S. states.' *Journal of International Economics* 56: 273-297.

De Santis, G. and Gerard, B. (1997). 'International asset pricing and portfolio diversification with time-varying risk.' *Journal of Finance* 52: 1881-1912.

Desgoits, A. (1999). 'Patterns of economic development and the formation of convergence clubs.' *Journal of Economic Growth* 4: 305-330.

Diamond, P. A. (1982). 'Aggregate demand management in search equilibrium.' *Journal of Political Economy* 90: 881-894.

Dickey, D. and Fuller, W. (1979). 'Distribution of the Estimates for Autoregressive Time Series With Unit Root.' *Journal of the American Statistical Association* 74: 427-431.

Durlauf, S. N. and Quah, D. T. (1999). 'The New Empirics of Economic Growth.' In: Taylor, J. and Woodford, M. (eds.), *Handbook of Macroeconomics*, Amsterdam, North-Holland, Amsterdam.

Durlauf, S. D. and Johnson, P. A. (1999). 'Multiple Regimes and Cross-Country Growth Behavior.' *Journal of Applied Econometrics* 10: 365-384.

Durlauf, S., Johnson, P. and Temple, J. (2005). 'Growth Econometrics.' In Aghion, P. and Durlauf, S. N. (eds.), *Handbook of Economic Growth.*Volume 1A, North-Holland, Elsevier, Amsterdam: 555-677.

Eckey, H.-F. (2001). 'Der wirtschaftliche Entwicklungsstand in den Regionen des Vereinigten Deutschlands.' *Volkswirtschaftliche Diskussionsbeiträge Universität Kassel* 20/01, ISSN 1615-2751.

Eldor, R., Pines, D. and Schwartz, A. (1988). 'Home asset preference and productivity shocks.' *Journal of International Economics* 25: 165-176.

Elhorst, J. P. (2003). 'Specification and Estimation of Spatial Panel Data Models.' *International Regional Science Review* 26: 244-268.

Egger, P. and Pfaffermayr, M. (2006). 'On the Role of Regional Spillovers for Beta- and Sigma-Convergence.' Forthcoming in *Papers in Regional Science.*

Eichengreen, B. (1990). 'One Money for Europe? Lessons from the U.S. Currency Union.' *Economic Policy* 10: 117-187.

Elliot, G., Rothenberg, T. and Stock, J. H. (1996). 'Efficient tests for an autoregressive unit root.' *Econometrica* 64: 813-836.

Epstein, P., Howlett, P. and Schulze, M.-S. (2003). 'Distribution dynamics: stratification, polarisation, and convergence among OECD economies, 1870-1992.' *Explorations in Economic History* 40: 78-97.

Evans, P. and Karras, G. (1996a). 'Convergence Revisited.' *Journal of Monetary Economics* 37: 249-265.

Evans, P. and Karras, G. (1996b). 'Do Economies Converge? Evidence from a Panel of US States.' *Review of Economics and Statistics* 78: 384-388.

Fiaschi, D. and Lavezzi, M. (2004). 'Nonlinear growth in a long-run perspective.' *Applied Economics Letters* 11: 101-104.

Fingleton, B. and López-Bazo, E. (2006). 'Empirical Growth Models with Spatial Effects.' Forthcoming in *Papers in Regional Science.*

Fotopoulos, G. (2005). 'Twin-Peaks in E.U. Regional Productivity Dynamics: A Nonparametric Analysis.' *mimeo.*

French, K. and Poterba, J. (1991). 'Investor diversification and international equity markets.' *American Economic Review* 81: 222-226.

Friedman, M. (1992). 'Do Old Fallacies Ever Die?' *Journal of Economic Literature* 30: 2129-2132.

Fujita, M., Krugman, P. R. and Venables, A. (2000). *The Spatial Economy.* MIT Press.

Funke, M. and Strulik, H. (2000). 'Regional Growth in West Germany: Convergence and Divergence?' *Economic Modelling* 16: 489-502.

Funke, M. and Strulik, H. (2000). 'Growth and Convergence in a Two-Region Model of Unified Germany.' *German Economic Review* 1: 363-384.

Hallett, H. A. J. and Ma, Y. (1993). 'East Germany, West Germany and their Mezzogiorno Problem: A Parable for European Economic Integration.' *Economic Journal* 103: 416-428.

Göcke, M. (2002). 'Various Concepts of Hysteresis Applied in Economics.' *Journal of Economic Surveys* 16: 167-188.

Grubel, H. G. (1968). 'Internationally diversified portfolios.' *American Economic Review* 58: 1299-1314.

Hansen, G. (1991). 'Hysteresis und Arbeitslosigkeit.' *Jahrbücher für Nationalökonomie und Statistik* 208: 272-298.

Hansen, B. E. (2001). 'The New Econometrics of Structural Change: Dating Breaks in U.S. Labor Productivity.' *Journal of Economic Perspectives* 15: 117-128.

Hatchondo, J. C. (2004). 'Asymmetric Information and the Lack of International Portfolio Diversification.' *mimeo.*

Hepp, R. and von Hagen, J. (2000). 'Regional Risksharing and Redistribution in the German Federation.' *ZEI Working Paper* B 15.

Hess, G. D. and Shin, K. (1998). 'Intranational Business Cycles in the United States.' *Journal of International Economics* 44: 289-313.

Hess, G. D. and van Wincoop, E. (eds.) (2000). *Intranational Macroeconomics.* Cambridge University Press, Cambridge.

Hobijn, B., Franses, P. H. and Ooms, M. (1998). 'Generalizations of the KPSS-test for stationarity.' *Econometric Institute Report*, no. 9802/A, Erasmus University, Rotterdam.

Hodrick, R. and Prescott, E. (1997). 'Post-war U.S. business cycles: An empirical investigation.' *Journal of Money, Credit and Banking* 29: 1-16.

Huberman, G. (2000). 'Home bias in equity markets: International and intranational evidence.' In: Hess, G. D., van Wincoop, E. (eds.), *Intranational Macroeconomics*. Cambridge University Press, Cambridge.

Huberman, G. (2001). 'Familiarity Breeds Investment.' *Review of Financial Studies* 14: 659-680.

Im, K. S., Pesaran, M. H. and Shin, Y. (2003). 'Testing for Unit Roots in Heterogeneous Panels.' *Journal of Econometrics* 115: 53-74.

Islam, N. (1995). 'Growth Empirics: A Panel Data Approach.' *Quarterly Journal of Economics* 110: 1127-1170.

Islam, N. (2003). 'What Have We Learnt from the Convergence Debate?' *Journal of Economic Growth* 17: 309-362.

Johnson, P. A. (2000). 'A nonparametric analysis of income convergence across the US states.' *Economics Letters* 69: 219-223.

Johnson, P. A. (2005). 'A continuous state space approach to 'Convergence by Parts'.' *Economics Letters* 86: 317-321.

Jüßen, F. (2006a). 'A Distribution Dynamics Approach to Regional GDP Convergence in Reunified Germany.' *mimeo*.

Jüßen, F. (2006b). 'Interregional Risk Sharing and Fiscal Redistribution in Reunified Germany.' Forthcoming in *Papers in Regional Science*.

Jüßen, F. (2006c). 'Home Bias, Neighborhood Bias, and Incomplete Capital Market Risk Sharing among US Federal States.' *mimeo*.

Kalemli-Ozcan, S., Sørensen, B. E. and Yosha, O. (2003). 'Risk Sharing and Industrial Specialization: Regional and International Evidence.' *American Economic Review* 93: 903-918.

Kalemli-Ozcan, S., Sørensen, B. E. and Yosha, O. (2004). 'Asymmetric Shocks and Risk Sharing in a Monetary Union: Updated Evidence and Policy Implications for Europe.' In: *Who will Own Europe? The Internationalization of Asset Ownership in the EU Today and in the Future*. Cambridge University Press.

Kang, S. J. (2004). 'The evolution of regional income distribution in Japan.' *Applied Economics* 36: 253-259.

Kapoor, M., Kelejian, H. H., and Prucha, I. (2006). 'Panel Data Models with Spatially Correlated Error Components.' Forthcoming in *Journal of Econometrics*.

Karolyi, G. A. and Stulz, R. M. (2003). 'Are Financial Assets Priced Locally or Globally?' In: Constantinides, M. H. and Stulz, R. (eds.), *The Handbook of the Economics of Finance*. North Holland, New York.

Kellermann, K. (1997). 'Finanzpolitik und regionale Konvergenz der Arbeitsproduktivitäten un der Bundesrepublik Deutschland.' *Finanzarchiv* 54: 232-260.

Kellermann, K. (2001). 'Interregionales Risk Sharing zwischen den deutschen Bundesländern.' *Applied Economics Quarterly* 47 (former *Konjunkturpolitik*, in German): 271-291.

Kilka, M. and Weber, M. (2000). 'Home Bias in International Stock Returns Expectations'. *Journal of Psychology and Financial Markets* 1: 176-193.

Koopmans, T. (1965). 'On the Concept of Optimal Economic Growth.' In: *The Econometric Approach to Development Planning*, Amsterdam, North-Holland.

Kosfeld, R., Eckey, H.-F. and Dreger, C. (2002). 'Regional convergence in unified Germany: A spatial econometric perspective.' In Dreger, C. and Galler, H. (eds.), *Advances in macroeconometric modeling*, Papers and Proceedings of the 3rd IWH Workshop in Macroeconometrics. Nomos, Baden-Baden.

Kosfeld, R. and Lauridsen, J. (2004). 'Dynamic Spatial Modelling of Regional Convergence Processes.' *Empirical Economics* 29: 705-722.

Krasnosel'skii, M. A. and Pokrovskii, A. W. (1989). *Systems with Hysteresis*, Berlin, Springer Verlag.

Kremer, M., Onatski, A. and Stock, J. (1999). 'Searching for prosperity'. *Carnegie-Rochester Conference Series on Public Policy* 55: 275-303.

Krugmann, P. (1991a). *Geography and Trade*. MIT Press, Cambridge (MA).

Krugmann, P. (1991b). 'Increasing Returns and Economic Geography.' *Journal of Political Economy* 99: 483-499.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P. and Shin, Y. (1992). 'Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?' *Journal of Econometrics* 54: 159-178.

Lane, P. D. and Milesi-Ferretti, G. M. (2001). 'The External Wealth of Nations: Measures of Foreign Assets and Liabilities for Industrial and Developing Nations.' *Journal of International Economics* 55: 263-294.

Lane, P. D. and Milesi-Ferretti, G. M. (2003). 'International Financial Integration.' *CEPR Discussion Papers* No. 3769.

Lee, M., Longmire, R., Mátyás, L. and Harris, M. (1998). 'Growth convergence: some panel data evidence.' *Applied Economics* 30: 907-912.

Levin, A., Lin, C. F. and Chu, C. S. J. (2002). 'Unit Root Tests in Panel Data: Asymptotic and Finite Sample Properties.' *Journal of Econometrics* 108: 1-24.

Levine, R. and Renelt, D. (1992). 'A Sensitivity Analysis of Cross-Country Growth Regressions.' American Economic Review 82: 942-963.

Levine, R. and Zervos S. J. (1993). 'What We Have Learned about Policy and Growth from Cross-Country Regressions.' *American Economic Review* Papers and Proceedings 83: 426-430.

Lewis, K. (1996). 'What Can Explain the Apparent Lack of International Consumption Risk Sharing?' *Journal of Political Economy* 104: 267-297.

Lewis, K. K. (1999). 'Trying to Explain Home Bias in Equities and Consumption.' *Journal of Economic Literature* 37: 571-608.

Liu, Z. and Stengos, T. (1999). 'Non-linearities in Cross Country Growth Regressions: A Semiparametric Approach.' *Journal of Applied Econometrics* 14: 527-538.

López-Bazo, E., Vayá E., Mora, A. J. and Suriñach, J. (1999). 'Regional Economic Dynamics and Convergence in the European Union.' *Annals of Regional Science* 33: 343-370.

Mace, B. (1991). 'Full Insurance in the Presence of Aggregate Uncertainty.' *Journal of Political Economy* 99: 928-956.

Maddala, G. S. and Wu, S. (1999). 'A comparative Study of unit Root tests with panel data and a new simple test.' *Oxford Bulletin of Economics and Statistics* 61: 631-652.

Magrini, S. (2004). 'Regional (Di)Convergence.' In: Henderson, V. and Thisse, J.-F. (eds.), *Handbook of Urban and Regional Economics*, Volume 4, Amsterdam, New York and Oxford, Elsevier Science, North Holland.

Mankiw, G. N., Romer, D. and Weil, D. N. (1992). 'A Contribution to the Empirics of Economic Growth.' *Quarterly Journal of Economics* 107: 407-437.

Marston, S. T. (1985). 'Two views of the geographic distribution of unemployment.' *Quarterly Journal of Economics* 100: 57-79.

Martin, R. (1997). 'Regional Unemployment Disparities and their Dynamics.' *Regional Studies* 31: 237-252.

Mayergoyz, I. D. (1991). *Mathematical Models of Hysteresis.* Berlin, Springer Verlag.

Maza, A. and Villaverde, J. (2004). 'Regional disparities in the EU: mobility and polarisation.' *Applied Economics Letters* 11: 517-522.

Mélitz, J. and Zumer, F. (1999). 'Interregional and international risk-sharing and lessons for EMU.' *Carnegie-Rochester Conference Series on Public Policy* 51: 149-188.

Mossi, M. B., Aroca, P., Fernández, I. J. and Azzoni, C. R. (2003). 'Growth Dynamics and Space in Brazil'. *International Regional Science Review* 26: 393-418.

Newey, W. and West, K. D. (1994). 'Automatic Lag Selection in Covariance Matrix Estimation.' *Review of Economic Studies* 61: 631–653.

Niebuhr, A. (2001). 'Convergence and the effects of Spatial Interaction.' *Jahrbuch für Regionalwissenschaft* 21: 113-133.

Ng, S. and Perron, P. (1995). 'Unit root tests in ARMA models with data dependent methods for the selection of the truncation lag'. *Journal of the American Statistical Association* 90, 268-281.

Nickel, S. (1981). 'Biases in Dynamic Models with Fixed Effects.' *Econometrica* 49: 1417-1426.

Obstfeld, M. (1994a). 'Risk-Taking, Global Diversification, and Growth.' *American Economic Review* 84: 1310-1329.

Obstfeld, M. (1994b). 'Are Industrial-Country Consumption Risks Globally Diversifed?' In: Leiderman, L. and Razin, A. (eds.), *Capital Mobility: The Impact on Consumption, Investment, and Growth.* Cambridge University Press, New York.

Obstfeld, M. and Peri, G. (1998). 'Asymmetric shocks: Regional non-adjustment and fiscal policy.' *Economic Policy* 26: 207-259.

Overman, H. G. and Puga, D. (2002). 'Unemployment Clusters Across Europe's Regions and Countries.' *Economic Policy* 17: 115-147.

Pagan, A. and Ullah, A. (1999). '*Nonparametric Econometrics.*' Cambridge University Press, New York.

Papell, D. H., Murray, C. J. and Ghiblawi, H. (2000). 'The Structure of Unemployment.' *The Review of Economics and Statistics* 82: 309-315.

Perron, P. (1990). 'Testing for a Unit Root in a Time Series Regression with a Changing Mean.' *Journal of Business and Economic Statistics* 8: 153-162.

Perron, P. and Vogelsang, T. J. (1992). 'Nonstationarity and Level Shifts With an Application to Purchasing Power Parity.' *Journal of Business and Economic Statistics* 10: 301-320.

Perron, P. (1997). 'Further evidence on breaking trend functions in macroeconomic variables.' *Journal of Econometrics* 80: 355-385.

Pesenti, P. and van Wincoop, E. (2000). 'Can nontradables generate substantial home bias?' *Journal of Money, Credit and Banking* 34: 25-50.

Phillips, P. C. B. and Perron, P. (1988). 'Testing for a unit root in the time series regression.' *Biometrika* 75: 335-346.

Pittau, M. G. and Zelli, R. (2004). 'Testing for changes in the shape of income distribution: Italian evidence in the 1990s from kernel density estimates.' *Empirical Economics* 29: 415-430.

Pittau, M. G. and Zelli, R. (2005). 'Empirical Evidence of Income Dynamics Across EU Regions.' Forthcoming in *Journal of Applied Econometrics.*

Pittau, M. G. (2005). 'Fitting Regional Income Distributions in the European Union.' *Oxford Bulletin of Economics and Statistics* 67: 135-161.

Portes, R. and Rey, H. (2000). 'The Determinants of Cross-Border Equity Flows: The Geography of Information.' *Center for International and Development Economics Research, Working Paper Series* 1011.

Portes, R. and Rey, H. (2005). 'The determinants of cross-border equity flows.' *Journal of International Economics* 65: 269-296.

Quah, D. T. (1993). 'Galton's Fallacy and Tests of the Convergence Hypothesis.' *Scandinavian Journal of Economics* 95: 427-443.

Quah, D. T. (1996a). 'Twin Peaks: Growth and Convergence in Models of Distribution Dynamics.' *The Economic Journal* 106: 1045-1055.

Quah, D. (1996b), 'Empirics for economic growth and convergence.' *European Economic Review* 40: 1353-1375.

Quah, D. T. (1996c). 'Convergence Empirics Across Economies with (Some) Capital Mobility.' *Journal of Economic Growth* 1: 95-124.

Quah, D. T. (1997). 'Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs.' *Journal of Economic Growth* 2: 27-59.

Quah, D. T. (2001). 'Searching for prosperity: A comment.' *Carnergie-Rochester Conference Series on Public Policy* 55: 305-319.

Ramsey, F. (1928). 'A Mathematical Theory of Saving'. *Economic Journal* 38: 543-559.

Ravn, M. O. and Uhlig, H. (2002). 'On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations.' *Review of Economics and Statistics* 84: 371-376.

Razin, A. and Yuen, C.-W. (1997). 'Income convergence within an Economic Union: the role of factor mobility and coordination.' *Journal of Public Economics* 66: 225-245.

Reutter, M. (2000). 'Hysteresis in West German Unemployment Reconsidered.' *CESifo Working Paper* 240.

Rey S. J. and Montuori, B. D. (1999). 'US Regional Income Convergence: A Spatial Econometric Perspective.' *Regional Studies* 33: 143-156.

Rey, S. J. (2001). 'Spatial Dependence in the Evolution of Regional Income Distributions'. In: Getis, A., Mur, J. and Zoeller, H. (eds.) *Spatial Econometrics and Spatial Statistics.* Palgrave, Hampshire.

Rey, S. J. and Dev, B. (2006). '$\sigma-$Convergence in the Presence of Spatial Effects.' Forthcoming in *Papers in Regional Science.*

Roed, K. (1997). 'Hysteresis in Unemployment.' *Journal of Economic Surveys* 11: 389-418.

Rose, A. K. and Engel, C. (2002). 'Currency Unions and International Integration.' *Journal of Money, Credit, and Banking* 34: 1067-1089.

Rowthorn, R. and Glyn, A. (2003). 'Convergence and Stability in US Regional Employment.' *mimeo*, Cambridge University.

Ruppert, D., Sheather, S. J. and Wand, M. P. (1995). 'An Effective Bandwidth Selector for Local Least Squares Regression.' *Journal of the American Statistical Association* 90: 1257-1270.

Sala-i-Martin, X. and Sachs, J. (1992). 'Fiscal Federalism and Optimum Currency Areas: Evidence for Europe from the United States.' In: Canzoneri, M., Masson, P. and Grilli, V. (eds.), *Establishing A Central Bank: Issues in Europe and Lessons from the U.S..* Cambridge University Press, London, U.K.

Sarno, L. and Taylor, M. P. (1998). 'Real exchange rates under the current float: unequivocal evidence of mean reversion.' *Economics Letters* 60: 131-137.

Schalk, H. J. and Untiedt, G. (1996). 'Technologie im neoklassischen Wachstumsmodell: Effekte auf Wachstum und Konvergenz.' *Jahrbücher für Nationalökonomie und Statistik* 215: 562-585.

Seitz, H. (1995). 'Konvergenz: Theoretische Aspekte und empirische Befunde für westdeutsche Regionen.' *Konjunkturpolitik* 41: 168-198.

Shawky, H. A., Kuemzel, R. and Mikhail, A. D. (1997). 'International portfolio diversification: A synthesis and an update.' *International Financial Markets, Institution, and Money* 7: 303-327.

Sheather, S. J. and Jones, M. C. (1991). 'A reliable data-based bandwidth selection method for kernel density estimation.' *Journal of Royal Statistical Society* B 53: 683-690.

Shiller, R. J. (1993). '*Macro Markets: creating institutions for managing society's largest economic risk'*. Clarendon Lectures in Economics Series, Oxford University Press.

Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis.* Chapman and Hall, New York.

Solnik, B. (1974). 'An equilibrium model of the international capital market.' *Journal of Economic Theory* 8: 500-524.

Solow, R. M. (1956). 'A Contribution to the Theory of Economic Growth.' *Quarterly Journal of Economics* 70: 65-94.

Sørensen, B. E. and Yosha, O. (1998). 'International risk sharing and European monetary unification.' *Journal of International Economics* 45: 211-238.

Sørensen, B. E. and Yosha, O. (1999). 'Federal insurance of US states: an empirical investigation.' In: Razin, A. and Sadka, E. (eds.), *The Economics of Globalization: Policy Perspectives from Public Economics.* Cambridge University Press, Cambridge.

Sørensen, B. E., Wu, Y.-T., Yosha, O. and Zu, Y. (2005). 'Home Bias and International Risk Sharing: Twin Puzzles Separated at Birth.' *CEPR Discussion Paper Series* No. 5113.

Stockman, A. C. and Dellas, H. (1989). 'International portfolio nondiversification and exchange rate variability.' *Journal of International Economics* 26: 271-289.

Stockman, A. C. and Tesar, L. (1995). 'Tastes and Technology in a Two-Country Model of the Business Cycle: Explaining International Co-Movements.' *American Economic Review* 85: 168-185.

Strong, N. and Xu, X. (2003). 'Understanding the Equity Home Bias: Evidence from Survey Data.' *Review of Economics and Statistics* 85: 307-312.

Swan, T. W. (1956). 'Economic Growth and Capital Accumulation.' *Economic Record* 32: 334-361.

Temple, J. (1999). 'The New Growth Evidence.' *Journal of Economic Literature* 37: 112-156.

Tesar, L. and Werner, I. (1995). 'Home bias and high turnover.' *Journal of International Money and Finance* 14: 467-493.

Tortosa-Ausina, E., Pérez, F., Mas, M. and Goerlich, F. J. (2005). 'Growth and Convergence Profiles in the Spanish Provinces (1965-1997).' *Journal of Regional Science* 45: 147-182.

Townsend, R. M. (1994). 'Risk and Insurance in Village India.' *Econometrica* 62: 539-591.

van Kerm, P. (2003). 'Adaptive kernel density estimation.' *Stata Journal* 3: 148-156.

van Wincoop, E. (1999). 'How big are potential welfare gains from international risksharing.' *Journal of International Economics* 47: 109-135.

von Hagen, J. (1992). 'Fiscal Arrangements in a Monetary Union: Evidence from the U.S..' In: Fair, D. and de Boissieu, C. (eds.), *Fiscal Policy, Taxation, and the Financial System in an Increasingly Integrated Europe.* Kluwer, Boston, MA.

von Hagen, J. (2000). 'Fiscal Policy and Intranational Risk Sharing.' In: Hess, G. D. and van Wincoop, E. (eds), *Intranational Macroeconomics.* Cambridge University Press, Cambridge.

Yang, Z., Li, C., and Tse, Y. K. (2006). 'Functional form and spatial dependence in dynamic panels.' *Economics Letters* 91: 138-145.

Zhou, C. (1998). 'Dynamic portfolio choice and asset pricing with differential information.' *Journal of Economic Dynamics and Control* 22: 1027-1051.

Zivot, E. and Andrews, D. (1992). 'Further evidence on the Great Crash, the oil price shock and the unit root hypothesis.' *Journal of Business and Economic Statistics* 10: 251-270.

# Appendix A

# Appendix to Chapter 2

**Univariate tests** Since the literature is inconclusive which unit-root test has the best sampling properties, we have considered the Phillips and Perron (1988) test as an alternative to the ADF test. As it can be seen from Table (A.1), the results obtained with the Phillips and Perron (1988) tests agree with the ADF tests for all federal states. We can reject the null hypothesis of non-stationarity only for one series (Rheinland-Pfalz).

To further examine the robustness of the results obtained with univariate tests, we have employed the KPSS (1992) test for stationarity. The KPSS test differs from the ADF or Phillips and Perron tests by having a null hypothesis of stationarity.[1]

Table A.2 summarizes the results of the KPSS test. The qualitative results are well compatible with the results of the ADF and Phillips and Perron tests. There is only one federal state (Hessen), for which the null hypothesis of stationarity can only be rejected at the 10 percent level. For all other federal states, we can reject the null at least at the 5 percent level of significance. Surprisingly, the series for Rheinland-Pfalz, which was found to be stationary according to the ADF and Phillips and Perron tests, is found to be non-stationary by the KPSS test.

**Panel-based tests** As can be seen from Table A.3, the Fisher-type tests show a different pattern than the LLC, IPS, and Breitung and Meyer tests. According to these tests the data is non-stationary. These results indicate that the overall results obtained with the panel-based tests are somehow ambiguous.

[1] To determine the optimal number of lags in the KPSS regression, we used the automatic bandwidth selection procedure proposed by Newey and West (1994). The autocovariance function was weighted by the Quadratic Spectral kernel. According to Hobijn, Franses, and Ooms (1998), the combination of the automatic bandwidth selection option and the Quadratic Spectral kernel yields the best small sample test performance.

Table A.1: Phillips and Perron test for relative unemployment rates (without trend)

| Federal State | Phillips-Perron $\hat{\mu}$ | $\hat{\rho}$ | $p$-value | Federal State | Phillips-Perron $\hat{\mu}$ | $\hat{\rho}$ | $p$-value |
|---|---|---|---|---|---|---|---|
| BW | -.101 | .942 | 0.538 | NRW | .083 | .908 | 0.577 |
| | (.071) | (.051) | | | (.055) | (.064 | |
| BY | -.074 | .958 | 0.761 | RP | -.070 | .599 | 0.034** |
| | (.051) | (.045) | | | (.062) | (.130) | |
| BRE | .283 | .918 | 0.735 | SAAR | .361** | .702 | 0.150 |
| | (.201) | (.065) | | | (.157) | (.112) | |
| HH | .188 | .875 | 0.559 | SH | .278** | .759 | 0.186 |
| | (.134) | (.080) | | | (.133) | (.107) | |
| HE | -.032 | .808 | 0.211 | $ur_{Ger}$ | .312* | .965 | 0.730 |
| | (.050) | (.093) | | | (.197) | (.037) | |
| NS | .105 | .892 | 0.362 | | | | |
| | (.072) | (.070) | | | | | |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively.
Standard errors in parentheses.

Table A.2: KPSS tests for level stationarity of relative unemployment rates

**KPSS-test (1992)**

| Federal State | lag | test statistic | Federal State | lag | test statistic |
|---|---|---|---|---|---|
| BW | 2 | $.892^{***}$ | NRW | 2 | $1.04^{***}$ |
| BY | 2 | $1.37^{***}$ | RP | 2 | $0.765^{***}$ |
| BRE | 2 | $1.33^{***}$ | SAAR | 2 | $1.23^{***}$ |
| HH | 2 | $1.22^{***}$ | SH | 2 | $0.588^{**}$ |
| HE | 2 | $.401^{*}$ | $ur_{Ger}$ | 2 | $1.51^{***}$ |
| NS | 2 | $.645^{**}$ | | | |

critical values for $H_0$

| 1% | 2.5% | 5% | 10% |
|---|---|---|---|
| 0.739 | 0.574 | 0.463 | 0.347 |

taken from KPSS (1992)

*,**,*** significant at the 10, 5 and 1 percent levels, respectively.

Table A.3: Madalla and Wu and Choi tests for a unit root in relative unemployment rates

| Maddala and Wu (1999) test | | | | Choi (2001) | | | |
|---|---|---|---|---|---|---|---|
| Lags | Obs. | $\chi^2\,(20)^a$ | $P > X$ | Lags | Obs. | $\chi^2\,(20)^a$ | $P > X$ |
| 0 | 420 | 24.26 | 0.23 | 0 | 420 | 24.26 | 0.23 |
| 1 | 410 | 20.33 | 0.44 | 1 | 410 | 23.98 | 0.24 |
| 2 | 400 | 20.60 | 0.42 | 2 | 400 | 24.77 | 0.21 |
| 3 | 390 | 15.41 | 0.75 | 3 | 390 | 23.72 | 0.25 |
| 4 | 380 | 15.77 | 0.73 | 4 | 380 | 24.01 | 0.24 |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively.
[a] The test statistic is distributed Chi-squared under the null.

Nonetheless, the weaker rejection of the unit-root hypothesis rather strengthens our main claim. This is that one needs to take into account a structural break in the data around 1980 to properly specify the model. Concerning the panel-based tests, the overall conclusion we arrive at is that these tests suggest a slow speed of convergence at best.

**Structural break tests** We also checked the robustness of the results obtained with the structural break tests with respect to the lag-length selection. We tried AIC and BIC to select the lag length as an alternative to the Ng and Perron (1995) sequential $t$-test method which we use in the paper. The results are summarized in Tables A.4 and A.5.

Both information criteria tend to choose shorter lag lengths, but the estimated break points remain very similar. Most importantly, there is only one federal state for which we cannot reject the unit-root hypothesis on the basis of an information criterion, but could reject the unit root under sequential $t-$testing. This state is Hessen, for which the initially estimated break point was 1993. We discussed this break date as being hard to interpret and therefore we do not worry too much about this change.

For Bayern and Bremen, the levels of significance pejorate somewhat (from

5% to 10% level), but if we look at the $p$-values, we see that this is due to a marginal change from marginally below 5% to slightly above this level of significance. For example, the $p$-values for Bayern and Bremen under the BIC are 6.18% and 5.44%, respectively.

In particular, the estimated half-lifes of shocks do not increase by using a different lag selection criterion. In fact, the only change is that under BIC the estimated half-life of a shock decreases from 2 to 1 years for Hamburg. In summary, also the tests based on information criteria provide evidence for substantial mean reversion, once we control for a structural break.

Table A.4: Perron-Vogelsang unit-root tests, lag length selected by AIC

**Perron and Vogelsang (1992) test**

| Fed. State | $T_b$ [2] | $k$ [1] | $(\hat{\rho}-1)$ | $\hat{\delta}$ | Fed. State | $T_b$ [2] | $k$ [1] | $(\hat{\rho}-1)$ | $\hat{\delta}$ |
|---|---|---|---|---|---|---|---|---|---|
| BW | 79 | 1 | -0.20 | -0.27 | NRW | 80 | 6 | -0.72** | 0.78 |
| | | | $(-2.95)$ | $(-2.31)$ | | | | (-5.54) | (5.05) |
| BY | 80 | 0 | -0.48* | -0.79 | RP | 70 | 0 | -0.62* | -0.36 |
| | | | (-4.64) | (-4.54) | | | | (-4.72) | (-2.75) |
| BRE | 82 | 0 | -0.7* | 2.88 | SAAR | 75 | 0 | -0.77** | 1.23 |
| | | | (-4.72) | (4.49) | | | | (-5.36) | (4.32) |
| HH | 82 | 1 | -0.73** | 1.75 | SH | 72 | 0 | -0.40 | 0.39 |
| | | | (-5.22) | (4.96) | | | | (-3.36) | (2.37) |
| HE | 88 | 0 | -0.37 | 0.32 | $ur_{Ger}$ | 79 | 1 | -0.29 | 1.68 |
| | | | (-3.54) | (2.82) | | | | (-4.32) | (4.02) |
| NS | 78 | 2 | -0.31 | 0.27 | | | | | |
| | | | (-3.51) | (2.30) | | | | | |

| Critical Values[1,3] | 1% | 2.5% | 5% | 10% |
|---|---|---|---|---|
| $T_b$ chosen by min. $t_{(\hat{\rho}-1)}$ [2] | -5.86 | -5.37 | -4.99 | -4.55 |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively. $t$–statistics in parenthesis.

[1] Lag length $k$ chosen according to AIC, given a pre-specified maximum of $k = 8$;

[2] $T_b, k, \rho, \theta$ are obtained by minimizing the $t$-statistic on $(\hat{\rho} - 1)$;

[3] Obtained from the empirical distribution of 5000 replications of a Monte Carlo experiment.

Table A.5: Perron-Vogelsang unit-root tests, lag length selected by BIC

**Perron and Vogelsang (1992) test**

| Fed. State | $T_b$ [2] | $k$ [1] | $(\hat{\rho}-1)$ | $\hat{\delta}$ | Fed. State | $T_b$ [2] | $k$ [1] | $(\hat{\rho}-1)$ | $\hat{\delta}$ |
|---|---|---|---|---|---|---|---|---|---|
| BW | 79 | 1 | -0.20 | -0.27 | NRW | 80 | 5 | -0.58** | 0.63 |
| | | | $(-2.95)$ | $(-2.31)$ | | | | (-5.04) | (4.50) |
| BY | 80 | 0 | -0.48* | -0.79 | RP | 70 | 0 | -0.62* | -0.36 |
| | | | (-4.64) | (-4.54) | | | | (-4.72) | (-2.75) |
| BRE | 82 | 0 | -0.70* | 2.88 | SAAR | 75 | 0 | -0.77** | 1.23 |
| | | | (-4.72) | (4.49) | | | | (-5.36) | (4.32) |
| HH | 83 | 1 | -0.86** | 2.04 | SH | 72 | 0 | -0.40 | 0.39 |
| | | | (-5.14) | (4.78) | | | | (-3.36) | (2.37) |
| HE | 88 | 0 | -0.37 | 0.32 | $ur_{Ger}$ | 79 | 1 | -0.29 | 1.68 |
| | | | (-3.54) | (2.82) | | | | (-4.32) | (4.02) |
| NS | 79 | 0 | -0.21 | 0.23 | | | | | |
| | | | (-2.37) | (1.86) | | | | | |

| Critical Values[1,3] | 1% | 2.5% | 5% | 10% |
|---|---|---|---|---|
| $T_b$ chosen by min. $t_{(\hat{\rho}-1)}$ [2] | -5.61 | -5.25 | -4.91 | -4.53 |

*,**,*** significant at the 10, 5, and 1 percent levels, respectively. $t$–statistics in parenthesis.

[1] Lag length $k$ chosen according to BIC, given a pre-specified maximum of $k = 8$;

[2] $T_b, k, \rho, \theta$ are obtained by minimizing the $t$-statistic on $(\hat{\rho}-1)$;

[3] Obtained from the empirical distribution of 5000 replications of a Monte Carlo experiment.

# Appendix B

# Appendix to Chapter 3

## B.1 Univariate adaptive kernel estimation

Consider a random variable $Y$ with realizations $Y_i$, $i = 1, 2, 3, ..., n$. In our application, $Y$ is regional relative GDP per worker in a given year. This variable has a density, $f(Y)$, which we want to estimate from the sample. Following Silverman (1986) and the concise overview in Van Kerm (2003), the following algorithm is used to estimate adaptive kernel densities:

1. Calculate a pilot kernel density estimate, $\hat{f}_K(y)$, using a fixed bandwidth $h$ and a kernel function $K$, evaluated at some equi-spaced grid points $y$ :

   $$\hat{f}_K(y) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{y - Y_i}{h}\right).$$

   The fixed bandwidth $h$ is chosen to be

   $$h = 0.9An^{-1/5}, \tag{B.1}$$

   where $A = \min(\text{standard deviation, interquartile range}/1.34)$. This bandwidth criterion has been recommended by Silverman (1986, p. 48).

   A Gaussian kernel function is used for $K$ (Silverman, 1986, p. 43):

   $$K\left(\frac{y - Y_i}{h}\right) = \frac{1}{\sqrt{2\pi}} e^{-0.5\left(\frac{y-Y_i}{h}\right)^2}. \tag{B.2}$$

   It is widely accepted that the choice of the kernel function is not a crucial issue and has no substantial influence on the results.

2. At each observation $Y_i$, calculate a local bandwidth factor, $\lambda_i$, that is inversely related to the pilot density estimate

$$\lambda_i = \lambda(Y_i) = \left\{ \frac{\tilde{f}_\varepsilon}{\hat{f}_K(Y_i)} \right\}^{1/2}, \tag{B.3}$$

where

$$\tilde{f}_\varepsilon = \left\{ \prod_{i=1}^{n} \hat{f}_K(Y_i) \right\}^{1/n}$$

is the geometric mean of $\hat{f}_K(Y_i)$. The local bandwidth factors are proportional to the square root of the underlying density functions at the sample points and have unit geometric mean.

3. The local bandwidth factors $\lambda_i$ multiply the fixed bandwidth $h$ to calculate the adaptive kernel $\hat{f}_A(y)$ :

$$\hat{f}_A(y) = \frac{1}{nh} \sum_{i=1}^{n} \frac{1}{\lambda_i} K\left(\frac{y - Y_i}{\lambda_i h}\right),$$

where $K$ is the Gaussian kernel function

$$K\left(\frac{y - Y_i}{\lambda_i h}\right) = \frac{1}{\sqrt{2\pi}} e^{-0.5\left(\frac{y-Y_i}{\lambda_i h}\right)^2}. \tag{B.4}$$

Finally, we normalize the density $\hat{f}_A(y)$ so that the sum of the points at which the density is evaluated is one. This allows us to interpret the normalized densities as showing the probability of a realization of $Y$ in the grid interval.

## B.2 Bivariate adaptive kernel estimation

As described in Section 3.4.2, the stochastic kernel $g_\tau(z|x)$ is estimated by dividing the joint density of $z$ and $x$ by the marginal density of $x$. The following algorithm is used:

1. Estimate the joint density of $z$ and $x$ using a product Gaussian kernel and an equi-spaced square grid. The calculation of a Gaussian product kernel is straightforward because one can simply multiply two univariate

Gaussian kernels to obtain the product kernel for the joint density:

$$\hat{f}_K(x,z) = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{h_x\sqrt{2\pi}} e^{-0.5\left(\frac{x-x_i}{h_x}\right)^2} \frac{1}{h_z\sqrt{2\pi}} e^{-0.5\left(\frac{z-z_i}{h_z}\right)^2},$$

where $h_x$ and $h_z$ are the bandwidths calculated using (B.1) separately in each dimension.

2. Along the lines of Appendix B.1, calculate local bandwidth factors $\lambda_i$ that are inversely related to the *joint* density estimate $\hat{f}_K(x,z)$. As in the univariate case, the local bandwidth factors $\lambda_i$ are multiplied with the fixed bandwidths $h_x$ and $h_z$ to estimate the adaptive (joint) density of $z$ and $x$, $\hat{f}_A(x,z)$.

3. To get an estimate for the marginal distribution of $x$, the joint density $\hat{f}_A(x,z)$ is (numerically) integrated over $z$ :

$$\hat{f}(x) = \int_{-\infty}^{\infty} \hat{f}_A(x,z)dz.$$

4. The final estimate for $g_\tau(z|x)$ is obtained by dividing the joint density by the marginal density:

$$\hat{g}_\tau(z|x) = \frac{\hat{f}_A(x,z)}{\hat{f}(x)}.$$

## B.3 Standard deviation of the ergodic density

To estimate the standard deviation of the ergodic density, first define the expected value, $\bar{y}$:

$$\bar{y} = \sum_{i=1}^{p} y_i \cdot \frac{\hat{f}_A(y_i)}{\sum_{j=1}^{p} \hat{f}_A(y_j)},$$

where the $y_i$s are the equi-spaced grid points and $p$ is the number of grid points. In this formula, the density $\hat{f}_A(y)$ is normalized so that the sum of the points at which the density is evaluated is one.

The standard deviation, $\hat{\sigma}$, is then calculated as

$$\hat{\sigma} = \sqrt{\sum_{i=1}^{p} (y_i - \bar{y})^2 \cdot \frac{\hat{f}_A(y_i)}{\sum_{j=1}^{p} \hat{f}_A(y_j)}}. \tag{B.5}$$

If the grid is chosen finer and finer the standard deviation $\hat{\sigma}$ converges to the theoretical moment.

## Erklärung

Ich versichere, dass ich diese Dissertation selbständig verfasst habe. Bei der Erstellung der Arbeit habe ich mich ausschließlich der angegebenen Hilfsmittel bedient. Die Dissertation ist nicht bereits Gegenstand eines erfolgreich abgeschlossenen Promotions- oder sonstigen Prüfungsverfahrens gewesen.

Dortmund, den 30.05.2006