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The evolution of regional labor market disparities

Daniel Werner

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Daniel Werner
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Chapter 1

1 Introduction

Large regional disparities are a common feature of the labor market in many countries. There are countries where full employment in certain regions coexists with mass unemployment in other regions (see, for example, the comprehensive overview in OECD 2000 and OECD 2005). Furthermore, the magnitude of regional labor market disparities within countries can be as large as between countries (see Elhorst 2003).

Regional labor market disparities appear to be less problematic and do not need to be a matter of great concern if they simply reflect the preferences of people (see OECD 2000). This could be the case if the differences between regions result from an uneven geographical distribution of regional amenities like an attractive climate or environment, a lower cost of living or better leisure-related endowments. The existence of such regional amenities might compensate low regional employment prospects. Thus, people might be encouraged to remain in regions characterized by regional amenities or move to such regions even if job opportunities are low and unemployment is high. In this case, regional labor market disparities are determined by the underlying preferences of people for certain regions and could represent an optimal equilibrium (see Marston 1985).

In contrast, regional disparities appear to be problematic if they are the result of economic distortion and market failure. In this case, regional labor market disparities are inefficient. A reduction of regional labor market disparities could lead to higher national output, lower inflationary pressure and could produce substantial social benefits (see, for example, the discussion in Elhorst 2003).

The economic theory provides various approaches to explain the existence of regional labor market disparities. First and foremost, regional labor market performance is determined by the demand for goods produced in a certain region. Hence, differences in the economic structure among regions is usually considered as an important origin of regional labor market disparities. Regions are characterized by high unemployment and low employment prospects if the demand for their regional products is low or depressed. This might be the case if the regional economic structure is characterized by a weak trading sector, industries that are no longer competitive, or industries that suffer a common decline in demand for their products.

According to neoclassical economic theory, regional labor market disparities induced by such demand-side factors should only be temporary. Higher regional unemployment as a result of a decline in demand for regional goods should lead to a decrease in regional wages. In a neoclassical framework, the combination of high unemployment and low wages leads to out-migration of people and in-migration of firms. People leave the depressed region and move to more dynamic regions with better employment prospects. Firms start to locate in the depressed region because wages are low and the pool of workers is large because of high regional unemployment. These firms create new jobs and the employment prospects in the depressed area increase. Hence, this adjustment mechanism should minimize the extent of regional labor market disparities. However, the existence of so called supply-side factors and institutional factors might be impediments to the adjustment process (see, for example, Baddeley/Martin/Tyler 1998).

Supply-side factors can be considered as the main reason why the mobility of people is constrained. Migration is only attractive if the employment opportunities in a more dynamic region provide viable alternatives for people from depressed regions. If the economic structure of a depressed region is characterized by old industries, it might be possible that the skills of workers from this region are not required in dynamic regions because they are outdated or redundant. Furthermore, the choice to migrate not only depends on employment prospects. For example, regional amenities, social ties or housing-market conditions influence the location decision of people. Hence, a dynamic region has to provide access to similar facilities and advantages beside job opportunities.

Wages can only serve as an adjustment mechanism if they exhibit a certain degree of flexibility. Baddeley/Martin/Tyler (1998) refer to factors that restrict wage flexibility as so called institutional factors. According to this definition, nationally uniform benefit levels, nationwide or industry wide wage rates and efficiency wages can be considered as institutional factors.

Moreover, the New Economic Geography introduced by Krugman (1991a) and Krugman (1991b) shows that economic activity might be unevenly distributed in space even if workers and firms are mobile and wages are highly flexibly. The New Economic Geography examines the spatial distribution of economic activity under the assumptions of monopolistic competition and agglomeration effects (economies of scale and external effects). If an additional firm locates in a certain region, this leads to a higher competition intensity on the goods market and the factor markets in this region. In a neoclassical framework, these two effects would induce out-migration of firms. However, if the regional economy is characterized by agglomeration effects, the location of an additional firm leads to an increase of the regional market size. This in turn allows the firms in the region to produce more efficiently and to realize higher profits. This so called home markets effect might compensate for the higher competition on the goods market and the factor market (see Krugman 1991b). Higher competition on the factor market implies higher factor prices and, therefore, higher wages. The increase in wages and a greater variety of goods in the region under consideration triggers in-migration of additional workers.

This in turn also leads to an increase of the regional market size. Thus, a circulative cumulative process might start and firms as well as workers tend to concentrate in certain regions. Hence, in a New Economic Geography setting, mobility of firms and workers does not lead to an adjustment of regional employment prospects across regions but instead increases regional labor markets disparities.

Hence, regional science provides a wide range of approaches to explain the existence of such regional labor market differentials. These conditions can occur in different combinations and interrelationships. At the same time, a large body of literature exists that empirically examines the origins of regional labor market disparities. Elhorst (2003) provides a comprehensive overview about theoretical and empirical explanations on regional unemployment differentials. The relationship between regional employment performance and agglomeration was, for example, analyzed by Combes (2000), Combes/Magnac/Robin (2004), Blien/Südekum/Wolf (2006), Dauth (2012), or Fuchs (2011). Although the empirical results are ambiguous, the literature provides detailed insights about the determinants of regional labor market performance.

However, these studies in general have little to say about the dynamics of regional labor market disparities. In order to get a complete picture about regional labor market disparities though, it is also necessary to consider the evolution of the object of investigation itself. Do regional disparities in labor market performance widen, narrow or remain constant over time? How stable is the geographical distribution of regional labor market performance?

The question of whether regional labor market disparities narrow or widen over time is related to the empirical phenomenons which are called convergence and divergence. Roughly speaking, convergence means that the differences between regions become smaller or even disappear over time. The main challenge of convergence analysis is to define a concept of convergence that is empirically testable.

The analysis of convergence processes has its roots in growth economics. Several concepts of convergence and suitable empirical procedures to test for the existence of convergence (or divergence) are provided by the economic growth literature (for an overview see Durlauf/Johnson/Temple 2005, 2009; for the specifics of regional convergence see Magrini 2004 and Rey/Le Gallo 2009). Many of the techniques developed in the economic growth literature to examine convergence, were adopted to examine the evolution of regional labor market disparities. This is possible because the concepts of convergence are characterized by a purely statistical nature. Hence, they are not only constrained to questions about economic growth but can also be applied (more or less easily) to other economic issues.

According to Baddeley/Martin/Tyler (1998), there are several ways to characterize the temporal evolution of regional labor market disparities. First, it is possible to examine whether the regional distribution of a labor market variable narrows, widens or remains constant over time by investigating the movements in the dispersion of this variable across regions. This approach refers to the concepts of β-convergence and σ-convergence. Regions exhibit β-convergence if poor or unfavorable regions exhibit higher growth rates than rich or favorable regions. In contrast, the concept of σ-convergence directly focuses on the inequality among regions by comparing the dispersion of a regional labor market variable at different points in time. Regions exhibit σ-convergence if the dispersion decreases over time.

A second approach is to examine the mobility of individual regions within the distribution of the regional labor market variable. This procedure refers to the so called distributional approach to convergence.

The third approach is to determine whether and to what extent there is any mean reversion of the differences between the regional labor market variables and their cross-sectional average (or their national counterpart respectively) over time. This approach refers to the concept of stochastic convergence introduced by Bernard/Durlauf (1995, 1996) and Evans/Karras (1996). The hypothesis of stochastic convergence can be examined using time series analysis.

The first two approaches described above belong to the group of convergence concepts which focus on the cross-sectional behavior of a regional indicator variable. In contrast, the third approach focuses on the time series behavior of the regional variables. The cross-sectional approach and the time series approach to convergence are based on different views of the nature of regional disparities and, therefore, provide different views of the convergence process.

There exists a strong connection between the cross-sectional approach to convergence and the neoclassical growth model. The neoclassical growth model implies that regions with a low initial value of output are characterized by a high marginal product of capital. Hence, these regions attract additional capital and grow faster than regions where the initial value of output is already high. This induces a transition process and the poor regions will catch-up with the other regions. The transition process comes to an end once all regions reach their steady state and the marginal product of capital is equal across the regions. In this case, regional disparities should be at a minimum or even disappear. This means that the underlying assumption of the cross-sectional approaches to convergence is that regional disparities simply reflect the differences in initial conditions. Thus, convergence is considered as a catching-up process between unfavorable and favorable regions.

However, a number of studies point out that persistent regional labor market disparities could also follow from regional labor market shocks which then lead to a (long-term) disequilibrium if the adjustment mechanisms are slow or weak (see, for example, Adams 1985, Marston 1985, Topel 1986, or Blanchard/Katz 1992). This implies that regions might not reach their equilibrium permanently or at least for a considerable period of time if economic disturbances have persistent and long-lasting effects on regional labor market performance. Hence, in this framework, regional disparities only decline if the effect of a shock is transitory and the regions (eventually) return back to their equilibrium. Therefore, it is also possible to consider convergence as an adjustment process after a region-specific shock.[1] Examples for region-specific labor market shocks are the closure of a large and important factory in a particular region or a downturn in an industry in which a particular region is specialized.

Following this point of view, regional development is no longer determined by differences in the initial conditions. Hence, the cross-sectional approach to convergence does not provide an adequate framework to examine the evolution of regional labor market disparities. Thus, another approach is necessary to examine the evolution of regional labor market disparities. If economic disturbances or changes in the economic climate are the main source of regional labor market disparities, the time series approach provides an adequate framework to test the hypothesis of convergence.

The adjustment processes after economic disturbances can be considered as an important determinant of the evolution of regional labor market disparities. This raises the question: How long does it take until things return back to "normal" after a region was hit by such a shock? In their seminal paper, Blanchard/Katz (1992) provide a theoretical and empirical framework to examine regional labor market dynamics after a region slumps or booms.

According to Blanchard/Katz (1992), regional slumps and booms are best described as transitory accelerations or slowdowns of regional employment growth. They identify region-specific labor demand shocks as the origin of such changes in employment growth.

Suppose a person loses his or her job in the course of a labor demand shock. This person can either remain unemployed in his or her area of residence, exit the labor force or leave the region. Therefore, regional labor market adjustment after a labor demand shock and mobility between these labor market states are very

1 Note, the literature distinguishes between region-specific and aggregate shocks. So called aggregate shocks affect all regions evenly. Therefore, an aggregate shock can not cause an increase or decrease in regional labor market disparities. In contrast, so called region-specific shocks affect regions differently. Hence, they can be considered as an important driving force in the development of regional disparities.

closely connected. Blanchard/Katz (1992) provide a fully specified empirical model that investigates the joint fluctuations in employment, unemployment, labor force participation and labor mobility to examine regional labor market dynamics and the adjustment processes after a region-specific labor demand shock.

This study investigates several aspects about the evolution of regional labor market disparities in Germany. It examines the hypothesis of convergence for regional employment and unemployment. Furthermore, it provides analysis about regional labor market dynamics after a region-specific labor demand shock.

1.1 Motivation

Nowadays, a number of studies exist which examine the evolution of regional labor market disparities. The large body of literature investigating the hypothesis of convergence focuses on regional unemployment disparities. In contrast, convergence analysis for regional employment disparities is scarce. Of course, measurable (negative) correlation between regional unemployment and regional employment exists. Nevertheless, movements in regional unemployment disparities and regional employment disparities are not necessarily symmetrical. The findings by OECD (2005) suggest for the case of France that an increase in regional unemployment disparities goes hand in hand with a decrease in regional employment disparities. For Germany, the opposite case is true. To get a complete characterization of the evolution of regional labor market disparities it appears to be reasonable to consider unemployment as well as employment. Hence, this study examines the convergence hypothesis for regional employment and regional unemployment in Germany.

The evolution of employment for most developed countries is characterized by rising inequalities between different qualification groups. Employment gains occur for high-skilled workers while the number of low-skilled workers decreases. This pattern is also observable on the German labor market. An increase in international competition promoting specialization in human-capital intensive industries (see Wood 1994, 2002), and skill-biased technological and organizational changes (see Lindbeck/Snower 1996, Acemoglu 1998, 2002, and Spitz-Oener 2006) are considered as the main sources of the change in the skill composition of employment.

The relationship between local skill composition and regional employment growth was investigated in several studies (see, for example, Glaeser/Scheinkman/Shleifer 1995, Simon 1998, Simon/Nardinelli 2002, Blien/Südekum/Wolf 2006, Shapiro 2006, Südekum 2008, or Schlitte 2011). The results of the studies indicate that regions with a large share of high-skilled workers exhibit a more favorable development of employment. The total number of employees in Germany was remarkably stable during the last two decades. The development of total employment seems to be mainly driven by business cycles. However, if high-skilled regions exhibit higher employment growth rates than low-skilled regions, while the number of employees in Germany remains stable, then this means that newly created jobs in one region go hand in hand with a loss of jobs in other regions. Hence, the changes in the employment prospects for workers with different skill levels seem to affect regional labor markets differently. Südekum (2008) points out that the change in the skill composition of the employees is more pronounced in regions which started with a relatively low share of high-skilled workers. This in turn implies that the change in the skill composition of employment goes hand in hand with a change in the geographical distribution of employment. However, it is far from clear whether this change in the geographical distribution of employment leads to increasing or decreasing regional employment disparities. Therefore, this study examines the relationship between the changes in the skill composition of employment and the evolution of regional employment disparities.

To get a comprehensive overview about the relationship between the change of skill composition of employment and the evolution of regional employment disparities, it appears to be necessary to consider skill-specific employment subgroups as well as total employment. Therefore, this study examines the hypothesis of convergence for total employment, high-skilled employment, medium-skilled employment and low-skilled employment.

Note, that investigating the hypothesis of convergence for different employment subgroups might also be rewarding for an additional reason. Employment subgroups could behave differently to aggregate employment. In this case, the analysis of regional total employment can only provide limited insights into the evolution of regional employment disparities. Divergence of total employment might simply reflect the divergent behavior of one employment subgroup only while all other employment subgroups show convergent behavior. Furthermore, it is possible that total employment shows convergent behavior even if several employment subgroups exhibit divergence. In this case, the geographical distribution of total employment might be stable. However, there would be a remarkable change in the geographical distribution of the employment prospects of the different subgroups. Hence, the analysis of employment subgroups might provide additional insights into the evolution of regional employment disparities.

However, the existing literature does not deal with the fact that *employees* are a heterogeneous group. Studies about the evolution of regional labor market disparities investigate the hypothesis of convergence for total (un)employment but provide no additional results for different subgroups. To the best of my knowledge, only Südekum (2008) tests the hypothesis of convergence for the regional share of high-skilled workers but provides no results for further employment subgroups.[2] Hence, the knowledge about the role of employment subgroups for the evolution of regional employment disparities is very limited. This study contributes to fill this gap.

The theoretical explanations of regional labor market disparities mentioned above highlight the role of economic disturbances in connection with sluggish adjustment processes as the origin of regional labor market disparities. Hence, considering convergence as an adjustment process after a region-specific shock seems to be more appropriate in a labor market context than considering convergence as a catching-up process between favorable and unfavorable regions. This might be one reason why the concept of stochastic convergence is very common when analyzing the evolution of regional labor market disparities. Up to now, there exist several studies testing the hypothesis of stochastic convergence for regional (un)employment (see, for example, Blanchard/Katz 1992 and Rowthorn/Glyn 2006 for the US, Decressin/Fatás 1995 for Europe, Möller 1995, Bayer/Jüßen 2007, Kunz 2012 for West Germany, Jimeno/Bentolila 1998 for Spain, Martin 1997 and Gray 2004 for the UK, Choy/Maré/Mawson 2002 for New Zealand and Debelle/Vickery 1998 for Australia).

The hypothesis of stochastic convergence requires that the effect of a shock on the deviations of a regional variable from its national counterpart is transitory and this measure shows mean reverting behavior. This means that the deviations of a regional variable from its national counterpart need to follow a stationary process. Unit roots are considered as the main source of non-stationarity of a time series. Therefore, usually unit root tests are applied to test the hypothesis of stochastic convergence.

A unit root test tests the null hypothesis of a unit root against the alternative hypothesis of a stationary process. Therefore, following this empirical approach to test for stochastic convergence, the null hypothesis corresponds to divergence (see also Pesaran 2007a). Strictly speaking, the rejection of the null hypothesis says that the regions do not show divergent behavior. However, the hypothesis of non-divergence and the hypothesis of convergence are not necessarily identical. For example, stability of the existing regional disparities is in line with regional non-divergence. Hence, if the hypothesis of a unit root can be rejected, this implies that regional disparities do not increase but not that they become negligible. Nevertheless, the existing literature interprets the rejection of a unit root in the deviations of regional variables from their national counterpart as evidence of

2 Grip/Hoevenberg/Willems (1997) also present results for employment subgroups. They test the hypothesis of convergence for two forms of atypical employment: part-time employment and temporary employment. Additionally, they present results for the various occupation groups in which part-time workers and temporary workers are employed. However, Grip/Hoevenberg/Willems (1997) test the convergence hypothesis for a cross-section of EU countries and do not choose a regional approach.

stochastic convergence. Also this study follows the literature and uses the term of stochastic convergence in this context. However, the crucial point that the alternative hypothesis corresponds to non-divergence rather than convergence should be kept in mind when interpreting the results.

Univariate unit root tests like the augmented Dickey-Fuller (ADF) test in general reject the hypothesis of stochastic convergence (see the findings in Blanchard/Katz 1992, Decressin/Fatás 1995, Jimeno/Bentolila 1998, Debelle/Vickery 1998, and Bayer/Jüßen 2007). However, the low power of univariate unit root tests to reject the hypothesis of a unit root is well known (see, for example, Campbell/Perron 1991, DeJong et al. 1992). By applying the unit root tests to a panel of cross-sectional units, it is possible to gain higher power. In contrast to the results from univariate unit root tests, the findings from these panel unit root tests in general favor the hypothesis of stochastic convergence.

Usually, the different findings are attributed to the higher power of the panel unit root tests compared to the univariate unit root test. However, the so called first generation panel unit root tests applied in the studies cited above are designed for a panel with independent cross-sectional units. Cross-sectional dependence might occur because of a movement common to all cross-sectional units. Examples are the business cyclical or technological change. As O'Connell (1998), Banerjee/Marcellino/Osbat (2004, 2005), and Baltagi/Bresson/Pirotte (2007) show, cross-sectional dependence within the panel leads to an over rejection of the non-stationarity hypothesis.

The so called second generation unit root tests provided by Bai/Ng (2004), Moon/Perron (2004), and Pesaran (2007b) relax the independency assumption. Carrion-I-Silvestre/German-Soto (2009) applied first and second generation panel unit root tests to investigate the hypothesis of stochastic convergence in terms of economic growth. The first generation panel unit root tests find evidence for the existence of stochastic convergence while the second generation panel unit root tests reject the hypothesis of stochastic convergence.

The results by Carrion-I-Silvestre/German-Soto (2009) show that the underlying properties of the cross-sectional units of the panel are essential for the appropriate test procedure to investigate the hypothesis of stochastic convergence. Therefore, the findings from the studies cited above applying first generation panel unit root tests should be interpreted with caution. To examine the evolution of regional labor market disparities, a detailed investigation of the assumption of cross-sectional independence appears to be necessary. This is done in this study.

In the case of stochastic convergence, the deviations of a regional variable from its national counterpart have to follow a stationary process. The literature provides different opportunities to calculate deviations of regional variables from their national counterpart: absolute differences, weighted differences or ratios (see, for example, Martin 1997 and Baddeley/Martin/Tyler 1998). These approaches differ in the assumption about the kind of the relationship between the regional variables and their national counterpart. Baddeley/Martin/Tyler (1998) point out that the assumption about the kind of this relationship could affect whether changes in regional disparities are observable. This in turn implies that the way deviations are calculated might also affect the results of a test for stochastic convergence. However, the existing literature does not deal with this fact. Hence, it is not clear how sensitive the results are with respect to the different assumptions about the kind of the relationship between regional variables and their national counterpart. This study investigates this aspect in more detail.

Blanchard/Katz (1992) provide a comprehensive framework to analyze the adjustment processes after a labor market shock. They identify unemployment, labor force participation and labor mobility as the main adjustment channels. However, in their study, labor mobility is restricted to migration and commuting as an additional form of labor mobility is neglected. This assumption appears to be reasonable if large regional units are considered where commuting only plays a minor role. However, for small regional units, the assumption of no or negligible commuting activities seems to be too restrictive. For the case of Germany, this might also hold for lager regional units. For example, Burda/Hunt (2001) point out that commuting has acted as a feasible substitute for out-migration for East German workers. This is the first study providing a more detailed look on the role of labor mobility during the adjustment process considering both commuting and migration.

Inflexible wages can be considered as an essential impediment for a quick adjustment process after a labor market shock. Therefore, changes in wages also represent an important adjustment mechanism. Several studies already analyze the role of the wage feedback during the adjustment process (see Blanchard/Katz 1992, Debelle/Vickery 1999, Choy/Maré/Mawson 2002, and Leonardi 2004). However, no results exist for Germany. Therefore, this study also examines the role of wages as an adjustment mechanism after a region-specific labor demand shock in Germany.

The existing literature identifies labor mobility as the most important adjustment mechanism in the long run but for some countries this even holds in the short run. Several studies argue that a strong relationship exists between the contribution of labor mobility to the adjustment process and the size of the regions under consideration (see Fredriksson 1999, Choy/Maré/Mawson 2002, or Kunz 2012). In general, more inter-regional labor mobility could be observed for small regions compared to large regions.

This leads to the question how the regional level should be chosen to capture the "real" adjustment dynamics. However, this seems to be rather a discussion about the appropriate delimitation of regions rather than the size of the regions. Studies on the dynamics of regional labor markets usually focus on administrative areas. But the borders of such areas are typically the results of political decisions or historical processes. In general, they do not reflect the distribution of economic activity in space or cannot be regarded as economically independent because functional labor markets extend across administrative borders. An analysis of the dynamics of regional labor markets neglecting spatial dependencies runs the risk of capturing only a part of the ongoing processes. From this point of view, a functional delimitation of regional labor markets appears more appropriate than an administrative delimitation. Hence, this study focuses on the functional delimitated regional planning units (Raumordnungsregionen) provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (Bundesinstitut für Bau-, Stadt- und Raumforschung – BBSR).

Blanchard/Katz (1992) suggest a vector autoregressive (VAR) model to investigate regional labor market dynamics after a region-specific labor demand shock. In most cases, the main interest is the response of the "average" region to a regional labor demand shock. Therefore, the data is usually pooled across cross-sectional units. This leads to a panel vector autoregressive (PVAR) model. Most of the existing studies following the approach suggested by Blanchard/Katz (1992) include region-fixed effects to account for unobservable regional heterogeneity and apply an ordinary least squares (OLS) estimator on the PVAR system. This procedure corresponds to estimating the coefficients of the PVAR by a least square dummy variable (LSDV) estimator.

Note, that the right hand side of each equation of the VAR contains lagged values of the left hand side variable. Therefore, pooling the data leads to a dynamic panel specification. However, a LSDV estimator in a dynamic panel framework is only valid if the number of observations in the time dimension gets large (see, for example, Nerlove 1967, 1971 and Nickell 1981). Even a large number of cross-sectional units does not overcome this problem. Usually, the time dimension is considered as large if observation in time for each cross-sectional unit exceeds the value of 30 (see, for example, the results in Judson/Owen 1999). The observations in the time dimension in most of the existing studies is considerably smaller than 30. Hence, the results of the existing literature might be subject to bias.

In addition, the panel in this study is characterized by a rather small number of observations in the time dimension. Binder/Hsiao/Pesaran (2005) introduced several estimators for a PVAR with a large cross-sectional dimension and a small time dimension. Mutl (2009) augments the estimation strategies introduced in Binder/Hsiao/Pesaran (2005) allowing for spatial dependence of the cross-sectional units in the error term. To avoid the problem described above, this study applies the estimation strategy suggested by Binder/Hsiao/Pesaran (2005) and Mutl (2009).

1.2 Structure of the thesis

Chapter 2 provides an overview of the literature on the evolution of regional labor market disparities. The various concepts of convergence applied to examine the evolution of regional labor market disparities are introduced and discussed in the first part of this chapter as well as the statistical and econometrical methodologies to test the hypothesis of convergence. Furthermore, the results of the studies are presented which examine the hypothesis of convergence in a labor market context.

The second part of chapter 2 provides an overview about the literature investigating adjustment processes after a labor demand shock. It introduces the theoretical and empirical framework developed by Blanchard/Katz (1992) to examine regional labor market dynamics and adjustment processes after a region-specific labor demand shock. Blanchard/Katz (1992) analyze adjustment processes after a regional labor demand shock for US federal states. Meanwhile, a number of studies exist adopting this framework for other countries and several studies augment the original approach. These studies are often called the regional evolutions literature in terms of the title of the seminal paper by Blanchard/Katz (1992). The findings of the regional evolutions literature are also discussed in chapter 2. Note, however, that Blanchard/Katz (1992) suggest a multivariate setting to analyze the adjustment processes after a regional labor demand shock. There exist several studies following an univariate approach to investigate the adjustment process after a region-specific labor market shock. The findings of these studies are also presented here.

Möller (1995), Baddeley/Martin/Tyler (1998), Bayer/Jüßen (2007), and Kunz (2012) already investigate the hypothesis of convergence for unemployment rates of West German federal states. However, even 20 years after reunification, a complete characterization of the evolution of regional unemployment disparities for Germany as a whole is still missing. So far, no study exists which considers both West and East Germany. Hence, chapter 3 examines the hypothesis of convergence for unemployment rates of all German federal states.

The different approaches to convergence do not necessarily enclose each other (see, for example, Barro/Sala-I-Martin 1991 and the examples given in Quah 1996b and Baddeley/Martin/Tyler 1998). Therefore, examining different concepts of convergence might lead to ambiguous results. Hence, studies analyzing the evolution of regional labor market disparities usually do not follow solely one approach. Also chapter 3 applies different approaches to get a complete picture of the evolution of regional unemployment disparities in Germany.

The results from the cross-sectional approaches to convergence show that the evolution of regional unemployment disparities does not seem to be characterized by a transition process but instead by changes in the economic climate. The time series approach appears to be more appropriate in this case. However, the choice of an appropriate test procedure to examine the hypothesis of stochastic convergence depends on whether the assumption of cross-sectional independence is valid. The findings from the tests provided by Pesaran (2004) and Ng (2006) show that the deviations of regional unemployment rates from their national counterpart suffer from cross-sectional dependence. Hence, a second generation panel unit root test is required. Here, the so called PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common Components) approach suggested by Bai/Ng (2004) is applied to test the hypothesis of stochastic convergence. Compared to other second generation panel unit root tests this approach is deemed to be the least restrictive. The tests for cross-sectional dependence by Pesaran (2004) and Ng (2006) as well as the PANIC approach by Bai/Ng (2004) are discussed in detail in chapter 3.

Stochastic convergence of regional unemployment rates requires that the deviations of the regional unemployment rates and the national unemployment rate follows a stationary process. The literature provides three different approaches to calculate these deviations. They differ in the assumption about the shape of the equilibrium relationship between the regional unemployment rates and their national counterpart. However, it is not clear how sensitive the results are with respect to these assumptions. To gain insight into this issue, chapter 3 provides results for all three approaches.

As mentioned above, regional unemployment disparities and regional employment disparities do not necessarily behave the same way. To provide a comprehensive overview of the evolution of regional labor market disparities, chapter 4 examines the hypothesis of convergence for regional employment rates. The aim of this chapter is to illustrate the relationship between the changes in the skill composition of employment and the evolution of regional employment disparities. Therefore, the hypothesis of convergence is investigated for total employment as well as for skill-specific employment. For this purpose, skill-specific regional employment rates are calculated for high-, medium-, and low-skilled employment. Moreover, the results presented in this chapter contribute to fill the gap about the role of employment subgroups and the evolution of regional employment disparities.

Please note, before reunification, the educational systems in East and West Germany show considerable differences. Thus, structural differences in skill levels of workers from East and West Germany are observable if they finished their education before reunification. For this reason, East German regions are excluded from the analysis and chapter 4 focuses on regions in West Germany only.

Chapter 4 applies cross-sectional approaches to convergence and examines the hypothesis of stochastic convergence. The traditional way of investigating the hypothesis of stochastic convergence in the case of regional employment rates would correspond to testing whether the deviations of the regional employment rates from the national employment rate follow a stationary process. Chapter 4 introduces an alternative way to test the hypothesis of stochastic convergence that provides several advantages compared to the traditional approach.

Banerjee/Wagner (2009) provide a comprehensive discussion about the structures and restrictions imposed by the definition of stochastic convergence. In the case of stochastic convergence, these restrictions have to be valid. Chapter 4 shows that the PANIC approach by Bai/Ng (2004) can be applied to examine whether this is case. To investigate directly the restrictions imposed by the definition of stochastic convergence appears to be a more convenient way to test the hypothesis of stochastic convergence compared to the traditional approach. The analysis for regional unemployment rates in chapter 3 shows that the results might be sensitive to the way the deviations of regional variables from their national counterpart are calculated. This alternative proceeding requires no assumption about the shape of the relationship between the regional employment rates and their national counterpart. Furthermore, it is possible to leave out the cross-sectional dependence test that is necessary for the choice of an adequate panel unit root test.

Chapter 5 examines regional labor market dynamics after a region-specific labor demand shock for West Germany and Germany as a whole. In contrast to previous studies, the analysis in chapter 5 is not based on administrative regional units but the more functional delimitated regional planning units are applied. A functional delimitation of regional labor markets appears to be more appropriate when investigating adjustment processes after a region-specific shock.

Most of the studies investigating adjustment processes after a region-specific labor demand shock identify labor mobility as the most important adjustment mechanism. However, labor mobility is restricted to migration whereas commuting as an additional form of labor mobility is neglected. This approach runs the risk of overestimating the role of migration during the adjustment process. Therefore, the framework by Blanchard/Katz (1992) is augmented by allowing for both commuting and migration. This allows more detailed insights into the role of labor mobility during the adjustment process compared to the previous studies. Furthermore, chapter 5 provides the first results about the role of wages during the adjustment process for regions in Germany. The PVAR estimator provided by Mutl (2009) is applied here to take into account the structure of the panel and the specification of the PVAR. The estimation strategy provided by Mutl (2009) is discussed in detail in chapter 5.

The last chapter summarizes the results of this study.

Chapter 2

2 What do we know about the evolution of regional labor market disparities?

By now, there exists a considerable body of literature examining the evolution of regional labor market disparities. The intension of this chapter is twofold. It provides an overview about the different approaches to investigate the evolution of regional labor market disparities. Furthermore, it presents the findings of the different studies following these approaches.

Section 2.1 deals with the question of convergence of regional labor market disparities. It introduces the different concepts of convergence applied in a labor market context and the empirical methodologies to test the hypothesis of convergence. Furthermore, it reviews the findings of the literature testing the hypothesis of convergence for regional labor markets.

Section 2.2 provides an overview about the literature investigating adjustment processes after a regional labor market shock. This section introduces the theoretical and empirical framework suggested in the seminal paper by Blanchard/Katz (1992) to investigate regional labor market dynamics after a region-specific labor demand shock. Furthermore, the section presents the results of the studies adopting or augmenting this framework. Besides these studies adopting the multivariate framework by Blanchard/Katz (1992) there also exist several studies that follow an univariate approach to examine the adjustment processes after a regional labor market shock. These studies are also reviewed in section 2.2.

This chapter shows that we know a lot about the evolution of regional labor market disparities. Nevertheless, there are still gaps and open questions. The aim of the following chapters of this study is to fill these gaps and to answer these questions.

2.1 The evolution of regional labor market disparities: Convergence or divergence?

The question whether regions are converging or diverging has its roots in growth economics. The economic growth literature provides various concepts of convergence and suitable empirical procedures to test the hypothesis of convergence (for an overview see, for example, Magrini 2004, Durlauf/Johnson/Temple 2005, 2009, or Rey/Le Gallo 2009). Many of these approaches to convergence were adopted to examine the evolution of regional labor market disparities. This is possible, because they are characterized by a purely statistical nature. Hence, these concepts of convergence are not only restricted to questions about economic growth but can also be applied to other economic issues.

In general, two broad threads of convergence analysis can be identified in the existing literature: the cross-sectional approach to convergence and the time series approach to convergence. Note, that these two approaches to convergence are predicated on different views of the nature of regional disparities and, therefore, different views of the convergence process. The cross-sectional approach considers convergence as a catching-up process between favorable and unfavorable regions. According to Bernard/Durlauf (1996), the cross-sectional approach to convergence appears to be appropriate if the regions under consideration are characterized by transition dynamics where the regions tend to converge to their steady state. As soon as all regions reach their steady state, regional disparities should minimize or even disappear. In this case, regional disparities simply reflect differences in the initial conditions. However, regional labor market disparities are often considered as the result of economic disturbances and sluggish adjustment processes after a region-specific shock. This in turn implies that regional disparities only disappear if a shock has only temporary effects and regions quickly return back to their steady state. Following this point of view, convergence can also be considered as an adjustment process after a region-specific shock. The time series approach to convergence deals with this aspect.

According to Bernard/Durlauf (1996), the time series approach has only poor power properties when applied to regions characterized by transition dynamics. If the regions under consideration are far from their steady state, the time series approach may falsely accept the hypothesis of divergence. In contrast, the cross-sectional approach to convergence might easily lead to misleading results if the development of regional disparities is mainly driven by changes in the economic climate and exhibits no clear trend. Therefore, the choice of the appropriate approach to test for convergence depends on the behavior of the regions under consideration (see Bernard/Durlauf 1996). Hence, studies analyzing the evolution of regional labor market disparities usually do not follow solely one approach. Instead, they investigate several approaches to get a complete picture about the evolution of regional labor market disparities.

This section provides an overview about the concepts of convergence which were applied to investigate the evolution of regional labor market disparities. Moreover, it reviews the findings of the existing literature. Reviews of the analysis of economic convergence are usually structured in a methodological way. This means they discuss the different concepts of convergence and present the findings of the studies using one method after the other. This appears reasonable because of the different nature of the existing concepts and, therefore, the different empirical methodologies that are required to test the hypothesis of convergence. This section is structured in the same way. Section 2.1.1 discusses the cross-sectional approaches to convergence and reviews the studies following these approaches. Section 2.1.2 introduces the time series approach to convergence. The last section outlines what we know about the evolution of regional labor market disparities based on the different approaches applied in the existing literature.

2.1.1 Cross-sectional approaches to convergence

The underlying assumption of cross-sectional approaches to convergence is that the regions under consideration differ in their initial conditions and are in transition towards their steady state (see Bernard/Durlauf 1996). In the case of convergence, the initial inequality in economic performance between regions disappears once all regions reach their steady state (under the assumption that all regions share the same steady state value). From this point of view, convergence can be considered as a catching-up process between unfavorable and favorable regions. Regional disparities simply reflect the differences in the initial conditions and are observable because the transition process is not yet finished.

If a catching-up process between favorable and unfavorable regions exists, then this implies that regions with a lower economic performance grow faster than regions with higher economic performance. In this case, a negative relationship between the initial condition or the initial value of the variable of interest and the corresponding growth rate must exist. The concept of β-convergence examines whether such a relationship exists among the regions. However, a negative relationship between initial values and growth rates is only a necessary but not a sufficient condition for closing the gap between favorable and unfavorable regions over time. Even if there is evidence of β-convergence, this does not mean differences in regional economic performance shrink and the regions become more equal over time. Therefore, the concept of β-convergence is often criticized. Hence, the concept of σ-convergence focuses directly on the evolution of regional inequality.

The concepts of β-convergence and σ-convergence was criticized by Quah in a series of papers (see Quah 1993a,b, 1996a,b,c,d) because they provide no information about the intra-distribution dynamics. Persistent inequality across regions can be consistent with marked changes in the intra-distribution of individual regions due to criss-crossing and leap-frogging (see the examples given in Quah 1996b and Baddeley/Martin/Tyler 1998). The distributional approach to convergence investigates the evolution of the entire cross-sectional distribution. This provides insights into aspects such as mobility, stratification and polarization of regions.

The concept of β-convergence

Two regions exhibit β-convergence if the one with the lower initial value grows faster than the other. The concept of β-convergence is closely linked to the models of the neoclassical growth theory. The procedure to empirically test the hypothesis of β-convergence can be directly derived from a neoclassical growth model (see, for example, Durlauf/Johnson/Temple 2009 or Barro/Sala-I-Martin 1992). Therefore, the neoclassical growth model serves as a starting point to introduce the concept of β-convergence.

The neoclassical growth model is based on the four variables output (Y), physical capital (K), labor (L) and the level of technology (A). Capital, labor and technology are combined to produce output. The production function for region i with $i = 1 \dots N$ is assumed to be of a Cobb-Douglas type. Furthermore, it is assumed that the production function is identical for all regions. The production function for region i at time t given by:

$$Y_{i,t} = K_{i,t}^{\alpha}(A_{i,t}L_{i,t})^{1-\alpha} \tag{2.1}$$

Due to the assumption of identical production functions across the regions, this means $\alpha_1 = \ldots = \alpha_N = \alpha$, differences in regional output can only occur because the amount of the input factors entering the production function differs across regions.

The product of the level of technology and labor ($A_{i,t}L_{i,t}$) can be interpreted as the efficiency unit of labor input. The production function in terms of effective units of labor can be obtained by dividing equation (2.1) by ($A_{i,t}L_{i,t}$). This leads to the following expression:

$$y_{i,t}^{E} = \left(k_{i,t}^{E}\right)^{\alpha} \tag{2.2}$$

where $y_{i,t}^{E} = Y_{i,t} / (A_{i,t}L_{i,t})$ and $k_{i,t}^{E} = K_{i,t} / (A_{i,t}L_{i,t})$.

Let $y_{i,\infty}^{E}$ denote the steady state value of output per effective unit of labor input for region i. Barro/Sala-I-Martin (1992) show that in a model with a Cobb-Douglas production function, the law of motion around the stable steady state for output per unit of effective labor can approximately be described by the following log-linear expression (for details see Barro/Sala-I-Martin 2004):

$$\log y_{i,t}^{E} = (1 - e^{-\beta_i t})\log y_{i,\infty}^{E} + e^{-\beta_i t}\log y_{i,0}^{E} \tag{2.3}$$

The parameter β_i characterizes the speed with which $y^E_{i,t}$ adjusts towards its steady state and $y^E_{i,0}$ denotes output per effective unit of labor input in the initial period 0.

The level of technology $A_{i,t}$ is unknown and unobservable. Hence, a model in terms of output per effective unit of labor can not be directly translated into a feasible empirical model. However, output per unit of labor $y_{i,t} = Y_{i,t} / L_{i,t}$ is observable and equation (2.3) can easily be rewritten in terms of this measure. Let g_i denote the constant rate of labor-augmenting technological progress and $A_{i,0}$ is the level of technology in the initial period. Therefore, the level of technology in period t is given by:

$$A_{i,t} = A_{i,0}e^{g_i t} \tag{2.4}$$

Using relationship (2.4) makes it possible to rearrange equation (2.3) as follows:

$$\log y_{i,t} - g_i t - \log A_{i,0} = (1 - e^{-\beta_i t})\log y^E_{i,\infty} + e^{-\beta_i t}(\log y_{i,0} - \log A_{i,0}) \tag{2.5}$$

Solving for output per unit of labor $y_{i,t}$ leads to the following expression:

$$\log y_{i,t} = g_i t + (1 - e^{-\beta_i t})\log y^E_{i,\infty} + (1 - e^{-\beta_i t})\log A_{i,0} + e^{-\beta_i t}(\log y_{i,0}) \tag{2.6}$$

The average growth rate of $y_{i,t}$ between the two points in 0 time and T is given by:

$$\gamma_i = T^{-1}(\log y_{i,T} - \log y_{i,0}). \tag{2.7}$$

Based on equation (2.6), the output per unit of labor for region i at date T denoted by $y_{i,T}$ can expressed as:

$$\log y_{i,T} = g_i T + (1 - e^{-\beta_i T})\log y^E_{i,\infty} + (1 - e^{-\beta_i T})\log A_{i,0} + e^{-\beta_i T}(\log y_{i,0}) \tag{2.8}$$

Subtracting $\log y_{i,0}$ from both sides of equation (2.8) and dividing both sides by T leads to the following expression for the average growth rate of output per labor γ_i:

$$\gamma_i = g_i + [(1 - e^{-\beta_i T}) / T]\log y^E_{i,\infty} + [(1 - e^{-\beta_i T}) / T]\log A_{i,0} - [1 - e^{-\beta_i T} / T]\log y_{i,0} \tag{2.9}$$

or:

$$\gamma_i = g_i + [(1 - e^{-\beta_i T}) / T](\log y^E_{i,\infty} + \log A_{i,0} - \log y_{i,0}) \tag{2.10}$$

Equation (2.10) shows that the growth rate γ_i can be decomposed into two parts. The first is growth due to technological progress g_i. The second is growth due to the closing of the initial gap between output per worker and the steady state value $y^E_{i,\infty}$ reflected by $(-1)[(1-e^{-\beta_i T})/T](\log y_{i,0} - \log y^E_{i,\infty} - \log A_{i,0})$. This part causes the catching-up process and, hence, convergence of the regions.

The literature mentions two convergence mechanisms (see, for example, Barro/Sala-I-Martin 2004 or Durlauf/Johnson/Temple 2009). If the position of an economy is well below the technological frontier, the catching-up process can be initiated by installing capital which corresponds to the current frontier of technology. However, more important in the economic growth literature is the role of diminishing returns to capital in the convergence process. Because of the diminishing returns to capital, a region starting with a relatively low level of output will grow relatively rapidly because its capital-output ratio is comparatively low and the marginal product of capital is high. This growth will slow down as the region reaches its balanced growth path and the marginal product of capital declines towards its steady state level. In contrast, the marginal product of capital is relatively low in a region with a high capital-output ratio. This leads to an average growth rate below the rate of technological progress in such regions.

Without making further assumptions, it is not possible to translate equation (2.10) into a feasible empirical model. $y^E_{i,\infty}$ and $\log A_{i,0}$ are both unobservable. Usually it is assumed that all regions share the same steady state so that $y^E_{i,\infty}$ can be described by a constant given by y^E_{∞}. For the initial value of technology $\log A_{i,0}$ the assumption is made that it can be decomposed into a constant part $\log A$ and differences across regions occur due to a cross-sectional specific shock ε_i. Under this assumption, it holds that $\log A_{i,0} = \log A + \varepsilon_i$. Furthermore, in equation (2.10), the growth rate of technological progress g_i as well as the speed of convergence are both region-specific terms. The economic growth literature often assumes that these two parameters are identical across regions. This means $g_i = g$ and $\beta_i = \beta$. Under these assumptions, equation (2.10) can be rewritten as:

$$\gamma_i = g + [(1-e^{-\beta T})/T)]\log y^E_{\infty} + [(1-e^{-\beta T})/T)]\log A_0 + (-1)[(1-e^{-\beta T})/T)]\log y_{i,0} + \varepsilon_i \quad (2.11)$$

Because the variables y^E_{∞}, A and g in equation (2.11) are considered as constants, it is possible to subsume them into a constant term c. This leads to the following regression equation to empirically test the hypothesis of β-convergence:

$$\gamma_i = c + (-1)[(1-e^{-\beta T})/T)]y_{i,0} + \varepsilon_i \quad (2.12)$$

Barro/Sala-I-Martin (1991) and Barro/Sala-I-Martin (1992) use a nonlinear least squares estimator to determine the speed of convergence β based on a regression of the form (2.12). A positive value for β is interpreted as evidence for the existence of β-convergence. In the case of β-convergence, the expression $(-1)[(1-e^{-\beta T})/T)]$ takes a negative value. This implies that there exists a negative relationship between the initial value of output per labor and the average growth rate γ_i. Therefore, regions with low initial levels of output per labor exhibit higher growth rates and grow faster than regions with high initial levels. This is the necessary condition to start a catching-up process.

Another possibility to directly examine the shape of the relationship between the average growth rate γ_i and the initial values $y_{i,0}$ is the following cross-sectional regression:

$$\gamma_i = c + \beta^* y_{i,0} + \varepsilon_i \tag{2.13}$$

where $\beta^* = (-1)[(1-e^{-\beta T})/T)]$. Also equation (2.13) makes it possible to determine whether a negative relation between the initial value in the initial period and the average growth rate exists. A negative value of the coefficient β^* in equation (2.13) can be interpreted as evidence for the existence of β-convergence. In contrast to regression (2.12), a regression of form (2.13) can be estimated using ordinary least squares. Note, the regression coefficient of equation (2.13) does not correspond to the speed of convergence β. Further transformation of the regression coefficient β^* is necessary to derive the speed of convergence β.

According to equation (2.12) and equation (2.13), the average growth rates only depend on the initial value and no other factors. This in turn implies that all regions converge to the same steady state value. In this case, β-convergence is said to be unconditional.

However, Barro/Sala-I-Martin (1991) and Barro/Sala-I-Martin (1992) point out that the neoclassical growth model predicts that the growth rate of a region is inversely related to the distance to its steady state value. Therefore, only if all regions share the same steady state is it to be expected that unfavorable regions grow faster than favorable regions. Otherwise, the negative relation between the growth rates and the initial values does not hold in a cross-sectional sample. The growth literature mentions for example differences in technological levels or differences in the saving rates as possible sources for different steady state values. Then a set of additional exogenous variables x_i^k has to be included in equation (2.13) to control for differences in regional steady state values:

$$\gamma_i = c + \beta^* y_{i,0} + \sum_{k=1}^{K} \beta^k x_i^k + \varepsilon_{i,T} \tag{2.14}$$

A negative value of the coefficient β^* in equation (2.14) is also interpreted as evidence of β-convergence. However, the specification of equation (2.14) implies that the steady state value differs among the regions. In this case, β-convergence is said to be conditional.

The regression approach to convergence introduced in this section is very popular in the empirical economic growth literature. Due to the strong linkage to the neoclassical growth model, it not only provides evidence of β-convergence, but also permits to test several theories of economic growth. However, no such strong association between a certain labor market model and the regression approach to convergence is depicted in the labor economic literature. Therefore, in a labor market context, the regression approach appears to be predominantly a statistical test for the relationship between the initial value of a variable and its growth rate. Furthermore, the existence of β-convergence does not imply that the inequality across regions diminishes over time. This issue will be discussed in more detail in the next section. This might explain why only three studies about the evolution of regional labor market disparities resort to the concept of β-convergence.

Pehkonen/Tervo (1998) test the hypothesis of β-convergence for regional unemployment rates in Finland. Their data sample includes data of 423 municipalities from the period 1975 to 1993. They estimate a cross-sectional regression of the form of equation (2.13) with the regional unemployment rate as an exogenous variable and its growth rate as the endogenous variable. To take the different development of Finnish unemployment over time into account, they provide results for diverse time periods. Their results give favor of unconditional β-convergence. However, additional robustness tests show that the assumption of different steady state values cannot be rejected. Like many other European countries, Finland also experienced a strong increase in unemployment since the 1970s. The findings by Pehkonen/Tervo (1998) suggest that the regions with low unemployment rates were more affected by this increase in unemployment.

Also Gil-Alana/del Barrio (2009) examine the hypothesis of β-convergence for regional unemployment rates. They consider 50 Spanish provinces and use quarterly data covering the time period from the third quarter 1976 to the fourth quarter 2004. They provide very detailed results for the hypothesis of β-convergence. Different starting points during the observation period are considered. Furthermore, growth rates are calculated for time periods of different length. Using the year 1976 as the starting point, no evidence of β-convergence was found. For the starting points in the 1980s and the 1990s the results are rather mixed whereas the regression results favor the hypothesis of β-convergence using the year 2000 as the starting point. Gil-Alana/del Barrio (2009) conclude that the labor market reforms in Spain in 1999 led to a reduction of the persistence differences of unemployment between regions. Note, however, if regions transit towards their steady state, the speed of convergence should decrease over time. However, the detailed analysis by Gil-Alana/del Barrio (2009) shows that the regression results favor the hypothesis of β-convergence if the considered observation period ends in the year 2000 or later but reject the hypothesis of β-convergence if the considered observation period ends before 2000. Furthermore, their findings indicate that the speed of convergence increases if the observation period increases. Hence, these results contradict the point of view that regional unemployment rates in Spain are characterized by a transition process towards their stead state.

Südekum (2008) empirically tests the so called smart city hypothesis for 326 districts in West Germany. Roughly speaking, the smart city hypothesis says that skilled cities exhibit higher employment growth rates. His study also provides results about conditional β-convergence of the regional skill composition of employees. Südekum (2008) applies a cross-sectional approach corresponding to equation (2.14) for the initial value of the share of high skilled workers (workers with completed tertiary education) and the corresponding growth rate. The growth rate of the share of high-skilled workers is computed for the period 1985 to 2002. The initial level of the share of high-skilled workers and additional regional control variables enter the right hand side of the regression with their value in 1977. The regression coefficient for the share of high skilled workers takes a high negative value and is highly significant. Hence, Südekum (2008) concludes that there is conditional β-convergence of the local skill composition.

The concept of σ-convergence

Because of the so called Galton's fallacy, it is not possible to conclude that a negative relationship between growth rates and initials values goes hand in hand with a fall in regional inequality. Galton investigates the relationship between the heights of parents and the heights of their children (see, for example, Galton 1886). According to his results, children tend to be larger than their parents if their parents are small and children tend to be smaller than their parents if their parents are large. This relationship can be considered as a form of β-convergence (see, for example, Barro/Sala-I-Martin1991). Galton (1886) infers that in terms of their heights, the generation of the children is "*always more mediocre*" than the generation of their parents. This would imply that a falling in the spread of heights in the population takes place in every new generation and the inequality in terms of heights decreases over time. However, this must not necessarily hold. The mistaken conclusion that regression towards means triggers a reduction of the dispersion is known as Galton's fallacy.

Bliss (1999) illustrates Galton's fallacy in terms of transition probabilities. He shows that even if not all tall parents have tall children, this does not mean that also the number of tall people decreases. Small and medium parents also have tall children that are then part of the tall population. The same holds for small parents and the small population. This example shows that the population can be characterized by β-convergence in terms of their heights, but this does not automatically trigger a reduction in the inequality of heights. Therefore, the existence of β-convergence might go hand in hand with stable or even increasing inequality across regions.

In convergence analysis, a reduction in the inequality across regions is called σ-convergence. In contrast to the concept of β-convergence, the concept of σ-convergence focuses directly on the evolution of inequality between regions in general by examining changes in the cross-sectional dispersion of an indicator variable over time. Two regions exhibit σ-convergence if the dispersion across the regions declines over time. If the dispersion increases over time the regions are said to diverge. Let $\sigma^2_{x,t}$ denote the dispersion across N regions of variable $x_{i,t}$ with $i = 1 \ldots N$ at date t. σ-convergence occurs between period 0 and period T if:

$$\sigma^2_{x,0} - \sigma^2_{x,T} > 0 \qquad (2.15)$$

To examine the hypothesis of σ-convergence, absolute measures for the dispersion such as the standard deviation are applied as well as relative measures such as the coefficient of variation. Although, the dispersion is the common inequality measure to test for σ-convergence, other measures of inequality such as the Gini coefficient or the Theil index can also easily be applied.

Note, that σ-convergence implies β-convergence but not vice versa. Therefore, the concept of β-convergence is often criticized and it is argued that this concept of convergence is irrelevant. However, Barro/Sala-I-Martin (1991) and Sala-I-Martin (1996) disagree with this point of view. They argue that the absence of σ-convergence is in line with a complete redistribution of regional economic performance where before unfavorable regions become favorable regions and vice versa. This process refers to the concept of β-convergence. Hence, Sala-I-Martin (1996) points out that the concept of β-convergence might also provide important information for policy makers.

OECD (2005)[1] investigates the inequality in regional unemployment rates and employment rates within and between 17 OECD countries comparing the years 1993 and 2003. As a measure for inequality, the coefficient of variation and the Theil index are used. Especially in Germany, Italy, Belgium and Turkey, disparities in regional unemployment rates and employment rates are very pronounced. In contrast, for Ireland, the Netherlands and Norway, the coefficient of variation

1 This study is an updated version of OECD (2000).

indicates that regional differentials in labor market performance in terms of employment and unemployment are comparatively low. The evolution of regional disparities in labor market performance is measured by changes in the Theil index. The findings suggest that within the OECD, the inequality within the countries only decreases slightly while differences between countries have been markedly reduced between 1993 and 2003. For the European countries, even a distinct increase in regional unemployment disparities within countries is observable and a slight increase in regional employment disparities within countries. However, this aggregate view on regions conceals that increasing regional disparities in labor market performance in Europe was mainly driven by Italy. Furthermore, the results in OECD (2005) indicate that the evolution of regional unemployment disparities and the evolution of regional employment disparities do not have to react symmetrically. For certain countries, the Theil index for the employment rate and the unemployment rate does not show the same sign. For example, for Germany the Theil index indicates an increase in regional employment disparities but a decrease in regional unemployment disparities. In contrast, for France, the opposite is true.

The findings by Overman/Puga (2002) suggest that the inequality in regional unemployment increased in Europe between 1986 and 1996. They consider 150 regions using level 2 regions according to the Nomenclature of Territorial Units for Statistics (NUTS). A Gini coefficient was calculated for relative regional unemployment rates[2] to measure the inequality across European regions. They find that the Gini coefficient was 19 percent higher in 1996 compared to 1986.

Baddeley/Martin/Tyler (1998) analyze the evolution of regional unemployment disparities across ten states of the European Union during the years 1981 to 1995. These are the United Kingdom (UK), (West) Germany, France, Italy and Belgium (the "core" EU(5)) as well as Spain, Denmark, the Netherlands, Ireland and Portugal (the "non-core" EU(5)). To analyze the evolution of regional unemployment disparities, they investigate the inequality of unemployment rates measured by the coefficient of variation. Their national-level analysis shows that the dispersion of unemployment rates between countries slightly increases up to the late 1980s and remains stable thereafter. This is the result of divergent behavior of the "non-core" EU(5) group while a slight convergence can be observed for the "core" EU(5) group.

Baddeley/Martin/Tyler (1998) also provide results of a regional-level analysis of the "core" EU(5) group. This restricted examination is enforced by data limitation. The regional-level analysis based on NUTS1, NUTS2 and NUTS3 level for the "core" EU(5) group shows for all three cases, that the coefficient of variation follows a

2 This means the regional unemployment is measured relative to the average European unemployment rate to annihilate common movement in regional unemployment rates. The computation of relative regional variables are discussed in detail in chapter 2.2.1.

clear cyclical pattern. The dispersion of regional unemployment rates increased until the beginning of the 1990s and then declined afterwards. In the mid 1990s, the dispersion of regional unemployment rates has returned more or less to values of the early 1980s. However, investigating the evolution of regional unemployment differentials for each country of the group separately on NUTS1 and NUTS3 level shows some interesting differences. This cyclical pattern can be found for Germany, Italy and the UK. In the case of France, the dispersion of regional unemployment rates appears to be stable over the whole observation period. In contrast to the other countries of the "core" EU(5) group the dispersion of regional unemployment rates in Belgium shows clear divergent behavior. To sum up, the dispersion of regional unemployment rates shows a high degree of overall stability and no tendency to narrow. The results of Baddeley/Martin/Tyler (1998) give no hint for the existence of σ-convergence in Europe.

Furthermore, Baddeley/Martin/Tyler (1998) follow an approach introduced by Chatterji (1992) and Chatterji/Dewhurst (1996) in growth economics that investigates the time series properties of the dispersion of a regional variable. Hence, this approach combines the concept of σ-convergence and time series analysis. They specify a variant of an autoregressive model for the variance of relative regional unemployment rates across regions in Europe. In this framework, an autoregressive parameter between -1 and 1 implies convergence, while an autoregressive parameter greater than one in absolute terms implies divergence. If the autoregressive parameter is equal to unity, this indicates stable relative regional unemployment rates fluctuating around a constant value. The hypothesis of an autoregressive parameter equal unity cannot be rejected for the regions of the "core" EU(5) group as a whole. This indicates persistent differences in regional unemployment for the time period under consideration. Baddeley/Martin/Tyler (1998) find similar results for Germany, France and Italy. Only for the UK they find an autoregressive coefficient statistically significant less than unity. However, Baddeley/Martin/Tyler (1998) argue that due to the size of the autoregressive parameter, the convergence process appears to be only weak. In contrast, for Belgium, the findings indicate a weak divergence process.

Martin (2001) examines convergence in regional productivity and regional employment growth on NUTS2 level considering 14 European countries (Austria, Belgium, Denmark, Finland, France, (West) German, Greece, Italy, the Netherlands, Norway, Portugal, Spain, Sweden and the UK) over the period 1975 to 1998. Changes in regional employment are expressed as the regional employment growth rate relative to the average employment growth rate of Europe. Note, that Martin (2001) does not compute an inequality measure to investigate the hypothesis of convergence. Instead, the regional relative employment growth rates refer to deviations around the European employment growth rate. If the inequality between regions becomes smaller, the deviation between the regional and the European employment growth rate should also decrease and, hence, the relative regional employment growth rate. Martin (2001) calculates cumulative employment growth rates for each region. The evolution of cumulative relative regional employment growth is considered on a country by country basis. The results show no evidence of regional convergence. Regional deviations from the European average appear to be persistent. Especially within Greece, Italy, Sweden, Spain and the UK, strongly divergent behavior can be observed.

Martin (1997) and Gray (2004) test the hypothesis of σ-convergence for regional unemployment rates in the UK. In contrast to Martin (1997), Gray (2004) excludes Northern Ireland from his analysis. The time series in Martin (1997) covers the period from 1965 to 1995. Gray (2004) uses monthly seasonally adjusted data covering the period from April 1974 to December 2002. Martin (1997) shows that the movements in the dispersion of relative regional unemployment rates are linked to the development of the national unemployment rate. The relative dispersion of regional unemployment appears to be inversely related to the national unemployment rate. Until the late 1980s, the absolute dispersion of regional unemployment rates tended to move directly with the national unemployment rate. However, in the 1990s, an inverse relationship is also observable for absolute dispersion. For the period from 1965 until 1975, a decrease in relative dispersion is observable which indicates σ-convergence during this period. However, the results of Gray (2004) show that the relative dispersion remains relatively stable from the mid 1970s until 2002. Both studies find a strong increase in absolute dispersion in the 1980s. However, in the 1990s the absolute dispersion returned back to its value of the 1970s and also remained very stable. Neither the absolute nor the relative dispersion of regional unemployment appear to follow a general upward or downward path which would indicate either a divergent or a convergent behavior of regional unemployment rates in the UK.

The fact that periods of convergence and periods of divergence alternate can also be found in other studies. The findings by Rowthorn/Glyn (2006) indicate that the employment rates of 48 US states exhibit periods of σ-convergence and divergence. From 1945 to the mid-1970s, the standard deviation of regional employment rates decreased. However, between then and the mid-1980s, an increase of the standard deviation is observable. After that the dispersion decreased again until the beginning of the 1990s and then remained on a stable level.[3]

3 Rowthorn/Glyn (2006) compare different sources of employment data. For an employment series provided by the Bureau of Economic Analysis no increase in the mid 1990s is observable. For all other sources only modest changes are observable.

Eichengreen (1990) investigates the evolution of the dispersion of the unemployment rate of the nine US census regions. Regional inequality is measured by the standard deviation and the coefficient of variation. Furthermore, the absolute difference between the highest and the lowest regional unemployment rate in each year is investigated. The results are quite striking and indicate that regional unemployment rates of US census regions show divergent behavior. Between 1960 and 1988, all inequality measures show a clear positive trend.

Debelle/Vickery (1998) and Dixon/Shepherd/Thomson (2001) provide results for the evolution of the dispersion of regional unemployment rates in Australia. Debelle/Vickery (1998) examine the six Australian states from 1978 to 1997. Dixon/Shepherd/Thomson (2001) examine seasonally adjusted quarterly unemployment rates covering the period second quarter 1978 to first quarter 1999 for the six states and the two territories in Australia. Debelle/Vickery (1998) show that the standard deviation indicates strong divergent behavior of Australian regional unemployment rates between the late 1970s and the late 1980s. In the 1990s, periods of decreasing and increasing regional dispersion are observable. However, during this period, the standard deviation reaches the low values of the early 1980s but never falls below them. Dixon/Shepherd/Thomson (2001) use the relative dispersion as a measure of regional inequality. They find a similar picture for the late 1970s and the 1980s. However, the relative dispersion markedly decreased in the early 1990s and then exhibits a positive trend until the end of the 1990s. Hence, both studies find no clear trend for the dispersion during the observation period. Furthermore, Dixon/Shepherd/Thomson (2001) find a negative long-run relationship between the relative dispersion of regional unemployment rates and the national unemployment rate in Australia. This means that periods of low unemployment rates are associated with a tendency for greater regional inequality in Australia (see also the results given in Dixon/Shepherd 2001).

The majority of the studies finds no evidence for the existence of σ-convergence. In general, periods of falling inequality alternate with periods of rising inequality. Especially in the case of the unemployment rate cyclical movements appear to be an important driving force for the development of regional inequality. If there was found a clear trend in the evolution of regional dispersion the results indicate for the existence of divergence.

The correct measure of the dispersion of a regional variable is not a trivial issue for the concept of σ-convergence. Variables with high average values usually show higher absolute dispersion than variables with low average values. Absolute measures of dispersion such as the standard deviations do not take this size effect into account. The unemployment rates of most of the developed countries exhibit a strong positive trend behavior during the last four decades. Today, their unemployment rates are several times higher compared to the 1970s. Hence, a rise in the absolute dispersion of regional unemployment rates over time could solely be the result of this strong increase in unemployment. This might explain why in Martin (1997) and Gray (2004), the standard deviation usually indicates an increase in the dispersion of regional unemployment rates especially in the 1970s and the 1980s in contrast to the coefficient of variation. Hence, the relative dispersion appears to be a more appropriate measure in a labor market context than the absolute dispersion (see also Martin 1997).

According to the neoclassical growth model, the transition process implies trend behavior of regional inequality and should trigger a fall in regional dispersion. This is also an underlying assumption of the definition of σ-convergence given in equation (2.15). Hence, the comparison of two points in time is only sufficient if the development of regional inequality shows such a trend and is not characterized by periods of falling and rising inequality. However, the majority of the studies examining the development of regional inequality over time find scarce evidence for a clear trend behavior but a strong dependence on cyclical movements in the case of regional unemployment rates. Therefore, comparing the inequality across regions only at two points in time, might lead to misleading results. In such a case, observing a rise or fall in regional dispersion could simply result from the time chosen for the two observation points during a business cycle. Hence, the results by OECD (2005) and Overman/Puga (2002) that only compare the degree of regional inequality in two different years have to be interpreted with some caution. According to these findings, it appears to be reasonable to investigate the evolution of regional dispersion over time at least in a labor market context.

As mentioned before, σ-convergence implies β-convergence. Hence, these findings have direct implications for the concept of β-convergence. The standard approach to test the hypothesis of β-convergence only focuses on the initial value of the variable of interest and the (average) growth rate for the whole observation period. Strictly speaking, the test for β-convergence according to equation (2.13) is only based on two points in time because it considers the average change of the variable of interest between the initial year and last year of the observation period. What happened between these two points in time is neglected. However, during this time period, the variable of interest might have gone through a very dynamic development even if the average growth rate is small. Thus, if the regions under consideration are not characterized by transition dynamics and changes in the dispersion of the variable of interest are mainly driven by changes in the economic climate, the concept of β-convergence might lead to misleading results. Similar to the case of σ-convergence, evidence of β-convergence also depends on where during the business cycle the initial year and the last year of the observation period are located. This could also explain the results by Gil-Alana/del Barrio (2009) when examining the concept of β-convergence for different starting points and different observation periods.

The distributional approach to convergence

The concept of β-convergence investigates the average behavior of the representative region while the concept of σ-convergence focuses on the evolution of the distribution across regions. Hence, both concepts only provide information about the transition of the regions towards their own steady states. They provide no insights into the dynamics of the entire cross-sectional distribution.

This drawback was criticized by Quah in a series of papers (see Quah 1993a,b, 1996a, b, c, d). He points out that the concepts of β-convergence and σ-convergence conceal issues such as mobility, stratification and polarization of regions. For example, persistent inequality across regions can be consistent with marked changes in the intra-distribution of individual regions due to criss-crossing and leap-frogging (see the examples given in Quah 1996b and Baddeley/Martin/Tyler 1998). Furthermore, Baddeley/Martin/Tyler (1998) show that complete rank-order stability of the regions due to a labor market variable can be associated with marked changes in the dispersion of this variable across regions. Hence, no inference can be drawn from the trend of regional dispersion on the intra-distribution dynamics and vice versa. Therefore, it is important to investigate the intra-distribution dynamics of the regions as well as the evolution of the dispersion across regions to shed light on these aspects.

OECD (2005) shows that the relative position of the regions in terms of their employment rate and unemployment rate does not change very much between 1993 and 2003. 80 percent of the European regions with a very high unemployment rate in 1993, still belong to the group of regions with a very high unemployment rate in 2003. The equivalent figure is about 65 percent in North America and less than 50 percent for regions in the Asia/Pacific area.

To get information about the intra-distribution dynamics, Martin (1997) and Baddeley/Martin/Tyler (1998) suggest testing the degree of rank-order stability of a regional labor market variable. They use Spearman's rank correlation coefficient to examine whether there are changes in the ranking of the regions due to their unemployment rates over time.

Baddeley/Martin/Tyler (1998) test the degree of rank-order stability for Belgium, France, Italy, Germany and the UK. They compare the correlation between the ranking of NUTS1 and NUTS3 areas respectively in 1983 and in subsequent years until 1995. Baddeley/Martin/Tyler (1998) conclude that distribution of regional unemployment in France, Italy, Germany and the UK has been characterized by a high degree of stability over time. In these four countries, the rank correlation of NUTS1 and NUTS3 regions decreases only slowly over time. For the NUTS1 regions, the correlation coefficient of the rank-order in 1983 compared to 1995 varies between 0.78 and 0.82. For the NUTS3 regions, the degree of rank-order stability is only slightly smaller. The correlation of the rank-order in 1983 compared to 1995 is still between 0.74 and 0.77. Only the Belgian regions appear to be more mobile within the distribution of regional unemployment rates. Compared to the other countries, the rank-order correlations decline faster. For Belgium, the rank-order correlation between 1983 and 1995 is 0.60 for the NUTS1 and 0.58 for NUTS3 regions. Compared to the findings by Eichengreen (1990) for US census regions, regional rank-order stability in terms of regional unemployment rates appears to be much smaller in the US than in Europe.

Martin (1997) and Gray (2004) confirm the result of a high rank-order stability of regional unemployment rates in the UK. Martin (1997) finds that the rank-order correlation of regional unemployment rates between 1980 and 1995 is 0.85. Gray (2004) finds a similarly high value for the correlation coefficient of the regional ranking in 1974 compared to 2002.

The degree of rank-order stability only provides information whether intra-distribution dynamics exist or not. However, if the test for rank-order stability indicates that regions are mobile within the distribution, one can not conclude which are the mobile regions. For example, changes in the cross-sectional distribution of regional unemployment rates might be caused by former high unemployment regions which became medium unemployment regions but also by former low unemployment regions which became medium unemployment regions.

Quah (1993a) and Quah (1996b) suggest using a Markov chain transition matrix to map the mobility of countries within the distribution of income per capita. This approach requires the assumption that the evolution of the income distribution can be described by a time-invariant and first-order Markov process. The countries under consideration are grouped into different categories according to their income per capita. These different groups are called income states. The Markov chain transition matrix provides information about the probability that a country from one income state transits to another state over time or remains in the same state. Hence, the transition matrix conceals, for example, what is the probability that a country from the group of countries with the lowest income per capita transits to the group of countries with the highest income per capita or how high the probability is that a poor country remains poor.

This approach was adopted by Pehkonen/Tervo (1998) to investigate the mobility of municipalities in Finland within the distribution of regional unemployment rates between 1975 and 1993. The analysis by Pehkonen/Tervo (1998) which is based on five unemployment states, leads to a 5 x 5 first-order Markov chain transition matrix. The different states are formed by grouping the municipalities into five equally sized categories according to their unemployment rates. The lowest category includes the 20 percent of municipalities with the lowest unemployment rates and the highest category includes the 20 percent of municipalities with the highest unemployment rates. Pehkonen/Tervo (1998) provide results for a short- and a long-run model.

The short-run model examines transition probabilities based on one-year transitions observed every year from 1975/1976 to 1992/1993. For the one-year horizon, they find only small transition probabilities between different states of unemployment. With 0.71, the overall probability of a municipality to remain in the same state turns out to be high. Pehkonen/Tervo (1998) conclude that in the short run, the level of persistence is very high. Therefore, in the short run, the probability is very limited for a municipality both to weaken or to improve its unemployment situation compared to other regions.

The long-run model is based on an 18-year transition from 1975 to 1993. In contrast to the short-run model, the long-run model shows higher transition probabilities. The overall probability of a municipality to remain in the same unemployment state decreases to 0.36. This means that between 1975 and 1993, 64 percent of all municipalities changed their unemployment state. Even transitions over two or three unemployment states are quite common. Hence, in the long-run, the behavior of municipalities appears to be less persistent and evidence of intra-distribution dynamics can be found. Furthermore, Pehkonen/Tervo (1998) find evidence that a connection exists between intra-distribution mobility and regional adjustment processes after a labor market shock. Municipalities located in regions where labor market shocks have long-lasting effects seem to show less intra-distribution mobility than municipalities located in regions where labor market shocks have only transitory effects.

Overman/Puga (2002) apply a three dimensional stochastic kernel to illustrate the transition probabilities of European NUTS2 regions between different states of unemployment between 1986 and 1996. They find evidence for polarization of regional unemployment rates within Europe. 81 percent of the regions with high unemployment rates relative to the European average in 1986, tend to have high unemployment rates in 1996. They find a similar picture for the regions with relatively low unemployment rates in 1986. 61 percent of the regions also remain in this group. In contrast, regions with medium unemployment rates in 1986 are very likely to exhibit a rise or fall in their unemployment rates relative to the European average until 1996.

According to Overman/Puga (2002), there are two different ways of thinking about the distribution of unemployment rates within Europe. On the one hand, unemployment might be first and foremost a national phenomenon. Countries exhibit different unemployment rates but regional unemployment rates within a country are identical. On the other hand, regional unemployment could be independent of national boundaries. In this case, the distribution of regional unemployment within each European country is quite similar to the distribution of regional unemployment within Europe as a whole. Of course, Overman/Puga (2002) point out that these are two very extreme points of view and rather hypothetical. In reality, the truth might be somewhere in between.

They apply the three dimensional kernel to regional unemployment rates measured relative to the European average and regional unemployment rates measured relative to their corresponding countries average for all eleven years. Overman/Puga (2002) show that regional unemployment disparities are more pronounced within countries than between countries. The results indicate that the distribution of unemployment rates within a country does not differ very much from the distribution of unemployment rates across Europe.

Furthermore, they show that there is a strong neighboring effect. They apply the three dimensional kernel to regional unemployment rates measured relative to the European average and regional unemployment rates measured relative to the average of the contiguous regions. Note, that these neighboring regions do not have to belong to the same country. The results show that a region's unemployment rate is very similar to that of its neighboring regions, irrespective of whether this region is characterized by high or low unemployment or whether a national border between regions exists or not. Hence, Overman/Puga (2002) conclude that variations in national institutions seem to explain only little of European regional unemployment disparities. Furthermore, neighboring regions in a foreign country could be more closely related to a region than regions in the same country.

The findings by the studies following the distributional approach to convergence indicate that regional unemployment rates in Europe are characterized by low intra-distribution dynamics. The distribution of regional labor market performance appears to be characterized by a high degree of persistence. Only some regions appear to improve or weaken their situation compared to other regions especially in the short run.

2.1.2 Time series approaches to convergence

The results of studies following the cross-sectional approach provide no evidence that the evolution of regional labor market disparities is characterized by clear convergent behavior. Furthermore, the findings of several studies examining the concept of σ-convergence for European countries indicate that changes in the regional inequality are not first and foremost driven by differences in the initial conditions but by changes in the economic climate. This makes it hard to assume that these regions are best characterized by a transition process towards their steady state. However, this is the underlying assumption of the cross-sectional approach to convergence.

In contrast, the underlying assumption of the time series approach to convergence is that region-specific shocks due to economic disturbances are responsible for the evolution of regional disparities. Regional labor market disparities do not reflect differences in the initial conditions. In this case, convergence can be regarded as an adjustment process after a region-specific shock rather than a catching-up process between favorable and unfavorable regions. Considering the results from the reviewed studies following the concept of σ-convergence, this point of view appears to be more appropriate in a labor market context.

The concept of stochastic convergence introduced by Evans/Karras (1996) and Bernard/Durlauf (1995, 1996) focuses on the time series behavior of the differences between regions in economic performance. In the case of stochastic convergence, a stable long-run equilibrium relationship between the regions exists and regional differences in economic performance should follow a stationary process. This means that region-specific shocks due to economic disturbances only have transitory effects on this relationship between regions. After a shock, the differences in economic performance between regions should return back to their initial value before the shock occurred. Methods of time series can be applied to test for stationarity and investigate the hypothesis of stochastic convergence.

The time series approach to convergence is largely statistical in nature and it allows precise statistical definitions about convergence. This is mentioned as an important advantage (see, for example, Durlauf/Johnson/Temple 2005, 2009). However, they also point out that the statistical nature of the time series approach is also a disadvantage because there is no explicit link to a theoretical model of economic growth. Note, this drawback from the perspective of growth theory makes it much easier to adopt this approach to other questions about convergence aside of economic growth.

This section introduces the concept of stochastic convergence. Furthermore, it describes the empirical methods to test the hypothesis of stochastic convergence and presents the results of the studies following the concept of stochastic convergence.

The concept of stochastic convergence

The discussion of stochastic convergence presented in this section is based on the definition of stochastic convergence given in Evans/Karras (1996). Let x denote the variable of interest. N regions are said to converge in this indicator variable x if, and only if, a common trend a_t and finite parameters μ_1, ..., μ_N exist so that:

$$\lim_{t \Rightarrow \infty} E(x_{i,t} - a_t) = \mu_i \tag{2.16}$$

for $i = 1$, ..., N and t denotes the time dimension. In this context, absolute convergence means that all $\mu_1 = \ldots = \mu_N = 0$. Hence, in the case of unconditional or absolute convergence, the indicator variable takes on the same value across all regions. If some $\mu_i \neq 0$ exist, convergence is called conditional. Stochastic convergence in the sense of definition (2.16) occurs if, and only if, the deviations of the regional variables $x_{i,t}$ from the joint trend a_t follow a stationary process. If all the deviations are non-stationary, the regions are said to diverge.

In the framework of Evans/Karras (1996) the joint trend a_t is allowed to follow a non-stationary process. If all regions share the same non-stationary joint trend, it can not be a source of divergence because the non-stationary trend is identical in every region. The existence of a non-stationary joint trend in the regional variable $x_{i,t}$ also implies that also the regional variables themselves might follow a non-stationary process. Therefore, stochastic convergence according to definition (2.16), does not require that the regions are in a stable equilibrium in terms of $x_{i,t}$. It only requires that there is a stable equilibrium relationship between the different regions. Note, this is not the case if there is an ongoing catching-up process between favorable and unfavorable regions. Therefore, the concept of stochastic convergence is not appropriate if the regions under consideration are characterized by transition dynamics.

To empirically test equation (2.16), the common trend a_t is needed. However, a_t typically is unknown and unobservable. To account for the unobservable joint trend, the average of the N regions is defined so that:

$$\lim_{t \Rightarrow \infty} E(\bar{x}_t - a_t) = \frac{1}{N}\sum_{i=1}^{N}\mu_i \tag{2.17}$$

where $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{i,t}$ is the average value of the indicator variable across the N regions. Defining the level of the common trend so that $\bar{x}_t - a_t = N^{-1}\sum_{i=1}^{N}\mu_i = 0$ and subtracting (2.17) from (2.16), leads to a definition of convergence based on the deviation of the regional series from the cross-sectional average:

$$\lim_{t \Rightarrow \infty} E(x_{i,t} - \bar{x}_t) = \mu_i \tag{2.18}$$

Stochastic convergence in the sense of equation (2.18) occurs if, and only if, the deviations of the regional variables from their cross-sectional average follow a stationary process. Therefore, the definition of stochastic convergence implies that region-specific shocks cannot explain the long-run behavior of the deviations between regional variables and their cross-sectional average or the differences between regions respectively. In general, $\bar{x}_t$ is interpreted as the national counterpart to $x_{i,t}$. This means that the hypothesis of stochastic convergence can be tested by examining whether the deviations of the regional variables from their national counterpart follow a stationary process.[4]

An underlying assumption of equation (2.18), is that the long-run relationship between $x_{i,t}$ and $\bar{x}_t$ is a linear one. However, the economic growth literature in general provides a definition of convergence corresponding to equation (2.18) using the logarithm of output or income. If $\log(x_{i,t})$ instead of $x_{i,t}$ enters equation (2.18), convergence occurs if the ratio between the regional variable and its national counterpart follows a stationary process because $\log(x_{i,t}) - \log(\bar{x}_t) = \log(x_{i,t}/\bar{x}_t)$. Note, that absolute convergence again requires that in the long run, the regional variable equals its national counterpart. Only in this case does the ratio equal one and μ_i becomes zero because log(1) = 0. Therefore, the definition of stochastic convergence is in line with different assumptions about the equilibrium relationship between regional variables and their national counterparts.

As Baddeley/Martin/Tyler (1998) point out, an initial issue in analyzing the evolution of regional disparities is the assumption made about the shape of the relationship between a regional variable and its national counterpart. Note, that a shock which leads to an equal absolute change in x_i and $\bar{x}$, does not affect the difference between the two variables but only the ratio. In contrast, a shock that leads to an equal relative change in the regional and the national variable, affects the difference of the two variables but not the ratio. Therefore, observing convergence or divergence can highly depend on the assumption made about the equilibrium relationship between x_i and $\bar{x}$.

To test definition (2.18), it is necessary to make assumptions about the shape of the equilibrium relationship between x_i and $\bar{x}$ in a first step. Based on these assumptions, the deviations between x_i and $\bar{x}$ have to be calculated. Computing the deviations of a regional variable from its national counterpart leads to measure

4 Note, if $x_{i,t}$ represents a relative variable such as for example the unemployment rate, the simple cross-sectional average $\bar{x}_t$ does not necessarily need to correspond to the national unemployment rate. If regions differ in size, the simple cross-sectional average gives too much weight to small regions. However, applied studies regard $\bar{x}_t$ as the national counterpart of a regional variable. This means that it is implicitly assumed that $\bar{x}_t$ corresponds to the weighted cross-sectional average rather than the simple cross-sectional average.

of x_i relative to $\bar{x}$. Therefore, the deviations of x_i and $\bar{x}$ are often called relative regional variables. The construction of such relative regional variables are discussed in detail in section 2.2.1.

A non-stationary time series that becomes stationary after taking first differences is said to be integrated of order one, denoted $I(1)$. Therefore, a stationary time series is said to be integrated of order zero, denoted $I(0)$. The terms non-stationarity and $I(1)$ as well as stationarity and $I(0)$ are usually used synonymously. Of course, it is possible that a time series is integrated of higher order but this case is not very relevant in economic applications. In their seminal paper, Nelson/Plosser (1982) show that many macroeconomic time series are non-stationary and follow an $I(1)$ process. Hence, in an economic context, non-stationarity is usually constrained to the $I(1)$ case. Note, that this study also follows this practice.

Studies investigating the hypothesis of convergence for regional labor market performance usually focus on the unemployment rate or, (less commonly), on the employment rate. The (un)employment rate is bound and can neither fall below 0 nor exceed 100 percent. If a bounded time series is near a barrier, the process reverts because it can not leave the bounds. In the case of an upper and a lower bound, the two barriers limit the excursion of the time series and induce mean reversion. Pesaran/Smith (1995) as well as Cross (1995) point out that one could expect that in the very long run, the bounded unemployment rate follows a stationary process. Pesaran/Smith (1995) show this for the unemployment rate of the UK and the US considering one century. Following this argumentation, (regional) (un)employment rates can not exhibit divergent behavior in the long run. Convergence analysis focuses on relative regional variables and not on absolute regional variables. Nevertheless, relative regional variables can also suffer from this problem.[5]

However, Nicolau (2002) points out that bounded time series can behave like a random walk even if they can not follow a true non-stationary process. In the case of an upper and a lower bound, the process is reflected by the two barriers and the process only appears to be stationary.[6] If the two bounds limit the excursion of the time series and induce mean reversion of the time series, this implies that a bounded time series might show a random walk behavior if the bounds are sufficiently far apart. Note, that neither the unemployment rate nor the employment rate tend to fluctuate between 0 percent and 100 percent even in the long run. Furthermore, in practice usually only a finite realization of the process is regarded and it is possible that during this sample period the considered variable can exhibit characteristics

5 For example, a relative regional unemployment rate computed as the difference between regional and national unemployment rate, can take values between -100 percent and +100 percent, at least hypothetically.

6 If the time series is characterized by a non-stationary behavior but the process is exogenously constrained by the bounds, the time series is said to follow a bounded $I(1)$ process (see, for example, Nicolau 2002).

that are not distinguishable from an unrestricted $I(1)$ process (see Dixon/Shepherd 2001 and Gray 2004).

Gray (2004) argues that the upward trend of the unemployment rate observable for many countries during the past decades, is inconsistent with a permanent rise that a deterministic trend would suggest because of the upper barrier. According to Gray (2004), it would be more appropriate to consider this movement as the result of a stochastic trend and to view the unemployment rate as $I(1)$, but without a deterministic trend. Therefore, in applied analysis, it appears to be reasonable to act as if the (un)employment rate and hence relative regional (un)employment rates potentially behave like unrestricted $I(1)$ processes (see also Dixon/Shepherd 2001).

As stochastic convergence implies that the deviations between regional variables and their national counterpart follow a stationary process, empirical testing for stochastic convergence corresponds to testing the hypothesis of (non)stationarity for relative regional variables. The time series literature provides different methods for such tests. These test procedures are discussed in the next sections.

Testing for a unit root and empirical application

Unit roots are considered as the main reason why a time series follows a non-stationary process. Investigating the existence of a unit root has a long tradition in time series analysis. Unit root tests test the null hypothesis of non-stationarity against the alternative hypothesis of stationarity. The so called Dickey-Fuller test for a unit root (DF test) introduced by Dickey/Fuller (1979) is based on a first order autoregressive process (AR process) given by:

$$x_t = \rho x_{t-1} + \varepsilon_t \tag{2.19}$$

Subtracting x_{t-1} from both sides of equation (2.19) leads to the following expression:

$$\Delta x_t = \varphi x_{t-1} + \varepsilon_t \tag{2.20}$$

where $\Delta x_t = x_t - x_{t-1}$ and $\varphi = \rho - 1$. The null hypothesis that the time series contains a unit root $\varphi = 0$ (respectively $\rho = 1$) is tested against the alternative hypothesis that the time series is stationary $\varphi < 0$ (respectively $\rho < 1$). This means the test for a unit root corresponds to a one-sided test for the coefficient in a so called Dickey-Fuller regression given by equation (2.20). To test the hypothesis of a unit root, the standard t-statistic can be applied given by:

$$DF = \frac{\hat{\varphi}}{se(\hat{\varphi})} \tag{2.21}$$

where $se(\hat{\varphi})$ corresponds to the usual OLS standard error from the Dickey-Fuller regression. However, under the null hypothesis of non-stationarity, the statistic does not follow a standard *t*-distribution but is skewed to the right. The critical values from this Dickey-Fuller distribution are smaller compared to the critical values form the *t*-distribution. This test referring to the critical values from the Dickey-Fuller distribution is often called the Dickey-Fuller *t*-test.

It is possible to allow for deterministic factors in the Dickey-Fuller regression by including an intercept δ and/or a deterministic trend τt.

$$\Delta x_t = \delta + \tau t + \varphi x_{t-1} + \varepsilon_t \tag{2.22}$$

To control for autocorrelation, lagged differences $\Delta x_{t-1}, \ldots, \Delta x_{t-K}$ can be added on the right hand side of equation (2.20). The optimal lag length K is usually determined by information criteria such as the Akaike Information Criterion (AIC) and Schwarz Information Criterion (BIC), or by a sequential *t*-test as suggested by Ng/Perron (1995). This leads to the so called augmented Dickey-Fuller test (ADF test). Additionally allowing for deterministic factors, the underlying regression of an ADF test is given by:

$$\Delta x_t = \delta + \tau t + \varphi x_{t-1} + \sum_{k=1}^{K} \phi_k \Delta x_{t-k} + \varepsilon_t \tag{2.23}$$

According to Pesaran (2007a), a crucial point should be kept in mind when using unit root tests to examine the hypothesis of stochastic convergence. The null hypothesis to be tested is that of non-stationarity or, in other words, divergence. Thus, if the null hypothesis is rejected, strictly speaking, one can only conclude that regional disparities exhibit no divergence and not that there exists convergence. Anyway, unit root tests are widely used to test the hypothesis of stochastic convergence.[7]

Blanchard/Katz (1992) find neither for regional employment growth rates nor regional unemployment rates of US states evidence of stochastic convergence. For the time period 1952 to 1990, the ADF test rejects the hypothesis of a unit root in relative regional employment growth rates only for three states on the five percent level. For relative regional unemployment rates, the hypothesis of a unit root is rejected on the five percent level only for three states for the time period 1972 to 1990.

The findings by Decressin/Fatás (1995) suggest that also for Europe the hypothesis of stochastic convergence in regional employment growth has to be rejected. Only for two of the 51 European regions under consideration does the

7 As discussed in the previous section, the (un)employment rate is a bounded variable. There exist so called unit root tests for bounded time series that test the null hypothesis of a unit root against the alternative hypothesis of a bounded $I(1)$ process (see, for example, Cavaliere 2002, 2005). This means that the null hypothesis as well as the alternative hypothesis is that of divergence. Hence, unit root tests for bounded time series do not provide an adequate framework to test the hypothesis of stochastic convergence.

ADF test reject the hypothesis of a unit root on the five percent level for the time period 1968 to 1987.

In contrast to the results provided by Decressin/Fatás (1995), the analysis in Jimeno/Bentolila (1998) for Spanish regions finds evidence of stochastic convergence in regional employment growth. For the time period 1977 to 1994 the hypothesis of a unit root is rejected for all regions under consideration except Cantabria. However, with respect to the regional employment rates, the ADF test indicates divergent behavior in Spain.

Bayer/Jüßen (2007) test the hypothesis of stochastic convergence for unemployment rates of West German federal states (excluding Berlin) covering the time span 1960 to 2002. The results of the ADF test clearly reject the hypothesis of stochastic convergence. With exception of Rhineland-Palatinate, the relative regional unemployment rates of West German federal states appear to contain a unit root.

However, Bayer/Jüßen (2007) find some evidence that the time series of relative regional unemployment rates exhibit structural breaks. As Perron (1990) points out, the traditional ADF tests performs poorly in the case of a structural break in the deterministic component of the time series. Bayer/Jüßen (2007) use the testing procedure provided in Perron/Vogelsang (1992) to account for structural breaks. Accounting for structural changes in the data clearly affects the findings. Now the hypothesis of a unit root is rejected for seven of the ten West German federal states. Only for Baden-Wuerttemberg, Lower Saxony and Schleswig-Holstein can the null hypothesis of a unit root still be not rejected.

To get information about the expected speed of convergence, Bayer/Jüßen (2007) additionally calculate the half-life of a shock in relative regional unemployment rates based on the regression results from the test by by Perron/Vogelsang (1992). The findings indicate that the half-life of a shock is three years for Northrhine Westphalia, two years for Bavaria and Hesse and one year for the other federal states.

For the regional labor market of New Zealand, Choy/Maré/Mawson (2002) find clear evidence of stochastic convergence regarding regional employment rates and regional employment growth rates. In addition to the ADF test, the Phillips-Perron test (PP test) introduced by Phillips/Perron (1988) is used. Whereas the ADF test uses additional lags of the first-differenced variable to account for serial correlation, the PP test uses robust standard errors introduced by Newey/West (1987). Both tests strongly reject the hypothesis that relative regional employment growth rates contain a unit root for all regions. The PP test also rejects the hypothesis of a unit root for relative regional employment rates.

Debelle/Vickery (1998) find evidence of stochastic convergence of regional employment growth rates in Australia. The ADF test rejects the hypothesis of a unit root for all regions under consideration. However, the results are less clear for the regional unemployment rates. For three of the eight regions under consideration the hypothesis of a unit root can not be rejected.

The findings from this univariate unit root tests are rather mixed. In the case of regional unemployment rates, the hypothesis of stochastic convergence has to be rejected whereas evidence of stochastic convergence is found for regional employment growth rates. However, the results by Blanchard/Katz (1992) and Decressin/Fatás (1995) for employment growth are somewhat surprising. It is common to remove a unit root in a time series by taking differences. Hence, growth rates are usually considered as stationary.

One reason why the univariate ADF test often fails to reject the hypothesis of a unit root, might be the low power of the test with regard to distinguishing the unit root hypothesis from the stationarity alternative hypothesis (see, for example, Campbell/Perron 1991, DeJong et al. 1992). Through the application of unit root tests to a panel of cross-sectional units, it is possible to gain higher power. This leads to the so called panel unit root tests.

Testing for a unit root in a panel and empirical application

The idea of panel unit root tests is to pool information from the several cross-sections (for an overview see Hlouskova/Wagner 2006, Breitung/Pesaran 2008, or Banerjee/Wagner 2009). Adding the cross-sectional dimension to the time series dimension means that non-stationarity from the time series can be dealt with and combined with the increased data and power that a cross-section brings. The cross-sectional dimension acts as repeated draws from the same distribution. Using the cross-sectional dimension of panel data increases the power of unit root tests that are based on a single draw from the population under consideration (see Harris/Sollis 2003).

Panel unit root tests were introduced by Levin/Lin/Chu (2002), Im/Peseran/Shin (2003), and Maddala/Wu (1999). They are based on a Dickey-Fuller regression which in the panel framework with $i = 1, \ldots, N$ cross-sectional units and $t = 1, \ldots, T$ time series units is specified as:

$$\Delta x_{i,t} = \varphi_i x_{i,t-1} + \varepsilon_{i,t} \tag{2.24}$$

where $\Delta x_{i,t} = x_{i,t} - x_{i,t-1}$. $\varepsilon_{i,t}$ is assumed to be independently distributed across i. As in the univariate case, an intercept δ_i and/or a deterministic trend $\tau_i t$ can be included to account for deterministic factors. Including lagged differences $\Delta x_{t-1}, \ldots, \Delta x_{t-K}$ to control for autocorrelation, leads to an augmented Dickey-Fuller equation in the panel framework given by:

$$\Delta x_{i,t} = \delta_i + \tau_i t + \varphi_i x_{i,t-1} + \sum_{k=1}^{K_i} \phi_k \Delta x_{i,t-k} + \varepsilon_{i,t} \tag{2.25}$$

The null hypothesis that all *N* series contain a unit root is given by $H_0 : \varphi_i = 0$ for all $i = 1, \ldots, N$. The literature considers two different alternative hypothesis. In the test procedure developed in Levin/Lin/Chu (2002) it is assumed that φ is identical for all cross-sectional units. The alternative hypothesis is given by: $H_1^a : \varphi_1 = \ldots = \varphi_N \equiv \varphi$ and $\varphi < 0$. H_1^a is called the homogeneous alternative.

The so called heterogeneous alternative introduced by Im/Peseran/Shin (2003) is less restrictive and more general than the homogeneous alternative. It allows for different autoregressive parameters. In this case, the alternative hypothesis is given by $H_1^b : \varphi_1 < 0, \ldots, \varphi_{N_0} < 0, N_0 \leq N$.

Breitung/Pesaran (2008) point out one should keep in mind when using panel unit root tests, that the null hypothesis is rejected if the series are stationary for at least one cross-sectional unit. Therefore, a rejection of the null hypothesis does not indicate that all time series are stationary. If the null hypothesis is rejected, one can only conclude that a significant fraction of the time series in the panel does not have a unit root.

By now, there exist various procedures to test for a unit root in a panel. Studies examining the hypothesis of stochastic convergence in a labor market context applied the tests provided by Levin/Lin/Chu (2002), Im/Peseran/Shin (2003), Breitung/Meyer (1994), Taylor/Sarno (1998), Maddala/Wu (1999), and Choi (2001). These tests are discussed briefly. Subsequently, the empirical results of the studies investigating the hypothesis of stochastic convergence by panel unit root tests are presented.

The approach introduced by Levin/Lin/Chu (2002) examines the hypothesis of a unit root against the homogeneous alternative. Because of the assumption of the null and the alternative hypothesis that all cross-sectional units share the same autoregressive coefficient, it is possible to pool the data to gain power. Levin/Lin/Chu (2002) suggest estimating φ based on a pooled regression. As they show, if equation (2.25) includes no deterministic factors under the null hypothesis, the derived regression *t*-statistics have a standard normal limiting distribution. However, if the regression includes deterministic terms, the *t*-statistic diverges to minus infinity. Therefore, Levin/Lin/Chu (2002) provide an adjusted *t*-statistic for the case of only an intercept and the case when there is both an intercept and a linear trend. In the framework by Levin/Lin/Chu (2002), the coefficient φ also has an economic interpretation. The autoregressive coefficient can be considered as a measure of the average speed of convergence. This is a major advantage of the approach by Levin/Lin/Chu (2002) compared to other panel unit root tests.

The test procedure suggested by Breitung/Meyer (1994) shows some parallels to the test introduced by Levin/Lin/Chu (2002). Homogeneous autoregressive coefficients for the cross-sectional units are assumed and the test is based on a pooled ADF regression including cross-sectional fixed effects. Breitung/Meyer (1994) show that OLS leads to consistent results under the null hypothesis of a unit root and that the results are biased under the stationary alternative. A t-test can be applied to test the null hypothesis.

Im/Peseran/Shin (2003) provide a procedure that tests the hypothesis of a unit root against the heterogeneous alternative. The idea of the test by Im/Peseran/Shin (2003) is to combine the ADF test statistics of univariate ADF tests for each cross-sectional unit. The so called t_{bar}-test suggested in Im/Peseran/Shin (2003) is based on the mean of the t-statistics from individual specific ADF regressions. Additionally to the group-mean t_{bar}-statistic, they also propose a group-mean Lagrange Multiplier test statistic.

The test provided by Taylor/Sarno (1998) allows for heterogeneous autoregressive parameters as in Im/Peseran/Shin (2003). The test is based on univariate j-th order autoregressive regressions for each of the N cross-sectional units which are considered as a system of N equations. It is suggested to estimate this system by a seemingly unrelated regression (SUR) estimator. The null hypothesis $H_0 : \sum_{j=1}^{J} \rho_{ij} - 1 = 0$ with $i = 1, \ldots, N$ where ρ_{ij} corresponds to the autoregressive parameters can be tested using the multivariate augmented Dickey-Fuller (MADF) statistic provided by Taylor/Sarno (1998).

The tests proposed by Maddala/Wu (1999) and Choi (2001) belong to the group of the so called Fisher-type tests. These tests combine the ρ-values ρ_i of the univariate ADF tests for each cross-sectional unit i with $i = 1, \ldots, N$. One advantage of this type of test is its flexibility. The test procedure makes it possible to combine univariate ADF tests with different deterministic factors. In contrast to the approach by Levin/Lin/Chu (2002), the test proposed by Im/Peseran/Shin (2003) and the Fisher-type tests provide no information about the speed of adjustment.

Consistency of estimation requires a careful selection of the lag length of the lagged endogenous variables $\Delta x_{i,t-1}, \ldots, \Delta x_{i,t-K}$ to account for serial correlation. Only if serial correlation is eliminated in the error term, $\varepsilon_{i,t}$ can it be considered as an asymptotically white noise process (see, for example, Banerjee/Wagner 2009). Note, that equation (2.25) permits the optimal lag length to vary across the cross-sectional units. The panel unit root tests provided by Levin/Lin/Chu (2002), Im/Peseran/Shin (2003), Maddala/Wu (1999), and Choi (2001) allow for this possibility. In the case of the tests suggested by Im/Peseran/Shin (2003), Maddala/Wu (1999), and Choi (2001), this is straightforward because they build on univariate ADF tests for every single cross-sectional unit. In the case of Levin/Lin/Chu (2002), the matter is more complicated because the test is based on pooled data. In a first step before pooling the data Levin/Lin/Chu (2002) suggest to transform $\Delta x_{i,t}$ and $x_{i,t-1}$ so that they are free of autocorrelation and deterministic factors. However, applied studies usually neglect the possibility that the choice of the optimal lag length could differ across the cross-sectional units. Results for different lag lengths are presented but it is often assumed that the optimal lag length is identical for every cross-sectional unit.

The findings by Choy/Maré/Mawson (2002) for New Zealand based on the test by Im/Peseran/Shin (2003) are in line with their findings based on univariate ADF tests. The panel unit root test rejects the hypothesis of a unit root for the relative regional employment growth rate and the regional employment rate. Also, Debelle/Vickery (1998) present results for Australia using the test by Im/Peseran/Shin (2003) next to the results from univariate ADF tests. The panel unit root test still rejects the hypothesis of a unit root for the regional employment growth rate, but now also for the relative regional unemployment rate. Both studies allow for heterogeneous lag lengths based on the BIC.

The study by Rowthorn/Glyn (2006) deals with the behavior of regional employment rates in US states. To test the hypothesis of stochastic convergence, the test by Maddala/Wu (1999) is applied. Maddala/Wu (1999) argue that selecting more than one additional lag in a panel framework would result in a loss of power and, hence, is not justified. Rowthorn/Glyn (2006) follow this argumentation and allow only for one additional lag for each cross-sectional unit. One aim of this study is to investigate how the choice of a certain data source influences the results. Therefore, the regional employment rate is calculated based on different data sources as well as for different time periods. Most of the tests without deterministic terms reject the hypothesis of a unit root in relative regional employment rates. Including a constant term, only relative regional employment rates based on the US census data appear to be stationary. Rowthorn/Glyn (2006) infer that the evolution of regional employment disparities in the US is characterized by absolute stochastic convergence rather than conditional convergence.

Möller (1995), Bayer/Jüßen (2007), and Kunz (2012) use panel unit root tests to test the hypothesis of stochastic convergence for regional unemployment rates of West German federal states. Kunz (2012) also presents results for the smaller district level.

Möller (1995) considers the time period 1960 to 1991. The procedure to test for a unit root in Möller (1995) is very similar to the approach by Breitung/Meyer (1994). He applies a pooled version of the ADF test and estimates a regression corresponding to equation (2.25). To account for serial correlation, up to three additional lags enter the ADF regression. No deterministic terms are included to the regression. If one or more lags are included in the ADF regression, the hypothesis of a unit root in relative regional unemployment rates is strongly rejected.

Bayer/Jüßen (2007) investigate the convergence hypothesis for regional unemployment rates for a longer time period covering 1960 to 2002. They apply various panel unit root tests. Including a constant term and allowing for up to four lags for each cross-sectional unit, the tests by Levin/Lin/Chu (2002), Im/Peseran/Shin (2003), and Breitung/Meyer (1994) reject the hypothesis of a unit root if two or less lags are included at least on the ten percent level. The test by Taylor/Sarno (1998) even reject the hypothesis of a unit root for each considered lag length. Bayer/Jüßen (2007) argue that the results for a specification with two lags is most preferable because in the univariate ADF tests, an optimal lag length of two appears on average as most appropriate. Following this argument, the results provide evidence of (conditional) stochastic convergence of regional unemployment rates. However, the tests by Maddala/Wu (1999) and Choi (2001) find no evidence of stochastic convergence.

In addition, Bayer/Jüßen (2007) also provide results for heterogeneous lag length across cross-sectional units. To determine the optimal lag length, the AIC, the BIC and the sequential *t*-testing method suggested by Ng/Perron (1995) are used. The results are rather mixed. If the optimal lag length is selected based on the BIC, the test by Levin/Lin/Chu (2002) and Im/Peseran/Shin (2003) reject the hypothesis of a unit root on the ten percent level. In the case of the AIC, both tests indicate that relative regional unemployment rates contain a unit root. In the case of the sequential *t*-testing method, the test by Levin/Lin/Chu (2002) rejects the hypothesis of a unit root, while the test by Im/Peseran/Shin (2003) does not. These results show that the findings of the panel unit root test might be very sensitive to the selection of the lag length.

The estimated autoregressive coefficient from the test by Levin/Lin/Chu (2002) provides information about the speed of convergence. The half-life time of shock can be calculated as $\log 0.5 / \log \rho$ with $\rho = \varphi - 1$. The results by Bayer/Jüßen (2007) indicate that the half-life of a region-specific unemployment shock in West German federal states is 5.57 years. This is much longer than the findings based on the test by Perron/Vogelsang (1992) discussed in the previous section. Bayer/Jüßen (2007) conclude that the existence of structural breaks leads to an upward bias of the half-life of the shock and, hence, the effect of a shock appears to be more persistent.

Kunz (2012) tests the hypothesis of stochastic convergence for West German federal states and districts. The time series covers the period from 1989 to 2004. The tests by Levin/Lin/Chu (2002) and Im/Peseran/Shin (2003) are applied including an intercept. The results provide clear evidence of (conditional) stochastic convergence in West German regional unemployment rates. Allowing for up to two lags in each cross-sectional unit, both tests reject the hypothesis of a unit root. Only for the specification with no additional lags does the test by Im/Peseran/Shin (2003) not reject the hypothesis of a unit root in the case of federal states. The half-life of a shock in relative regional unemployment rates are calculated based on the results of the test by Levin/Lin/Chu (2002). According to the findings in Kunz (2012), the half-life of a region-specific shock is 1.5 years in the case of federal states and 1.6 years in the case of districts. The average half-life of a shock for federal states is considerably smaller compared to the findings by Bayer/Jüßen (2007). But they are more in line with the findings by Bayer/Jüßen (2007) based on the test by Perron/Vogelsang (1992). Kunz (2012) argues that the absence of breaks during the observation period could be an explanation for this result.

Furthermore, Bayer/Jüßen (2007) and Kunz (2012) use a first order autoregressive AR(1) panel model to distinguish between conditional and unconditional convergence. The panel AR(1) model is specified for relative regional unemployment rates denoted by $\tilde{ur}_{i,t}$. It takes the following form:

$$\tilde{ur}_{i,t} = \alpha_i + \beta \tilde{ur}_{i,t-1} + \varepsilon_{i,t} \tag{2.26}$$

where i denotes the cross-section dimension with $i = 1, \ldots, N$ and t denotes the time dimension with $i = 1, \ldots, T$. The constant α_i can be interpreted as a regional fixed effect to account for (unobserved) regional heterogeneity. Only in the absence of regional heterogeneity convergence can be considered as unconditional. Therefore, it is possible to distinguish between conditional and unconditional convergence by testing the joint significance of the fixed effects. If an *F*-Test rejects the hypothesis that all fixed effects are insignificant, this is considered as evidence of conditional convergence. Otherwise, if the *F*-test fails to reject the hypotheses that all fixed effects are insignificant, this is considered as evidence of unconditional convergence. In both studies, the *F*-test rejects the hypothesis that all regional effects are equal zero for German federal states and in Kunz (2012) also for German districts. Bayer/Jüßen (2007) and Kunz (2012) interpret this result (in combination with the results from the unit root tests) as evidence of conditional stochastic convergence.

In contrast to the univariate unit root tests, the panel unit root tests favor the hypothesis of stochastic convergence for regional unemployment rates (and regional employment rates). However, the results by Bayer/Jüßen (2007) show that the panel unit root tests might be sensitive to the choice of additional lags to account for autocorrelation. Note, all panel unit root tests used in the studies reviewed in this section belong to the group of so called first generation panel unit root test. This means that these tests assume that the cross-sectional units are independent. None of the existing studies investigate whether this assumption holds. If this assumption is violated, the first generation panel unit root test might lead to misleading results. This should be kept in mind when interpreting these results (for more details about this issue see section 3.4).

Testing the co-integration relationship

Nelson/Plosser (1982) show that many macroeconomic time series contain a unit root. Nevertheless, it is often observable that non-stationary time series move closely together and the difference between them is stable. In this case, the time series are said to be co-integrated. If a regional variable and its national counterpart are both non-stationary but the difference between them is stable, then this is in line with with the definition of stochastic convergence according to equation (2.18). In the case that all regional time series for the N cross-sectional units are $I(1)$, the definition of stochastic convergence implies the existence of $N-1$ co-integration relationships (see Banerjee/Wagner 2009). Therefore, the hypothesis of stochastic convergence can also be tested by examining the co-integration relationship between the regional variable and its national counterpart.

Two variables which are both $I(1)$ are called co-integrated if there exists a linear combination of these two variables that is $I(0)$. In such a case, Engle/Granger (1987) define these two variables as co-integrated of order (1,0). For the case that a regional variable x_t and its national counterpart $\overline{x}_t$ are both $I(1)$, the concept of co-integration requires that the linear combination $(u_t = x_t - \beta\overline{x}_t)$ is $I(0)$ and, therefore, stationary. According to the framework provided in Engle/Granger (1987), the null hypothesis that x_t and $\overline{x}_t$ are co-integrated can directly be tested by investigating whether the residuals ε_t of the following regression are either $I(0)$ or $I(1)$:

$$x_t = \beta\overline{x}_t + \varepsilon_t \tag{2.27}$$

To test for stationarity, an ADF test can be applied on ε_t. Another possibility is the Co-Integrating Regression Durbin Watson (CRDW) test suggested by Sargan/Bhargava (1983). The CRDW test tests the null-hypothesis that the residuals from the estimated co-integration regression (2.27) follow a simple non-stationary random walk against the alternative of a stationary first order AR process.

Eichengreen (1993) tests for a co-integration relationship between regional unemployment rates and the national unemployment rate in the US (time period: 1962 to 1988), the UK (time period: 1961 to 1982) and Italy (time period: 1962 to 1985). For the UK and Italy, the CRDW test supports the hypothesis of co-integration. The findings suggest that in the year after a shock, on average about one half of the shock is eliminated in Britain and about one third in Italy. In contrast, the results for the US are rather mixed. Eichengreen (1993) argues that the difference could arise because the ranking of the regions according to the unemployment rate is more persistent in Europe than in the US. Therefore, a much more stable relationship between regional and the national unemployment rates can be expected in Europe compared to the US. Another reason might be that the time series under consideration are rather short.

The results provided by Martin (1997) and Byers (1990) for regional unemployment rates in the UK confirm the findings by Eichengreen (1993). For the time period 1965 to 1995, Martin (1997) finds strong evidence of a co-integration relationship. The CRDW test indicates that there is a co-integration relationship between every region and the national unemployment rate. Between one third and one half of the effect of the shock is eliminated after one year. Byers (1990) only considers the three regions North, Scotland and Wales for the time period 1949 to 1985. The results of ADF and CRDW tests suggest that a co-integration relationship between the unemployment rates of these three regions and the national unemployment rate exists.

In contrast, Chapman (1991) only finds weak evidence for a co-integration relationship between regional unemployment rates and the national unemployment rate in the UK during the time period 1974 to 1989. The results from the CRDW test do not support the hypothesis of co-integration, while the ADF test[8] indicates that a co-integration relationship between regional unemployment rates and the national unemployment rate exists for half of the regions.

In addition, Gray (2004) analyzes the co-integration relationship between regional and national unemployment rates in the UK. He uses seasonally adjusted monthly unemployment rates covering the time period April 1974 to December 2002. A bivariate analysis of the relationships between regions and the nation does not support the hypothesis of co-integration between regional unemployment rates and the national unemployment rate. This result is in line with Chapman (1991) but does not confirm the findings of Eichengreen (1993) and Martin (1997). Gray (2004) additionally follows the approaches suggested by Johansen (1991) and Johansen (1995) and applies the maximum eigenvalue and the trace statistic to test for the number of co-integration relationships. In contrast to the residual based approach, these multivariate approaches can examine the number of co-integration relationships for a set of regions. The results of a multivariate setting

8 However, Gray (2004) reinterprets these results in Chapman (1991). Therefore, the critical values provided by Engle/Yoo (1987) are used instead of the values given by Dickey/Fuller (1979) as in the original study. According to Gray (2004), the reinterpretation suggests that the hypothesis of co-integration is rejected for all regions except the Northern Region.

indicate that eight of the ten regions under consideration are co-integrated. Only East Midland and East-Anglia do not tend towards an equilibrium relationship with the other regions in the UK. Therefore, the multivariate setting reveals that regional unemployment rates in the UK are more closely associated than a bivariate investigation would suggest. Gray (2004) interprets these results as evidence of persistence in unemployment rate differentials. The relationships among the regional unemployment rates are characterized by natural different rates or long-run multiple equilibria.

Dixon/Shepherd (2001) examine whether the unemployment rates for the six states and the two territories in Australia are co-integrated. They use seasonally adjusted quarterly unemployment rates covering the period second quarter 1978 to first quarter 1999. Investigating the various pairwise combinations of the regions, they find mixed evidence. They conclude that the series are probably not co-integrated and that long-run movements in regional Australian unemployment rates do not appear to have followed a common trend path.

2.1.3 Convergence or divergence?

The previous sections introduced the different concepts of convergence investigated in a labor market context and their empirical implementation. The cross-sectional approach to convergence and the time series approach of convergence consider different aspects of the evolution of regional labor market disparities. The cross-sectional approach focuses on transition dynamics and convergence is considered as a catching-up process between favorable and unfavorable regions. The time series approach to convergence considers convergence as an adjustment process after a region-specific shock. Hence, these two approaches do not enclose each other. They consider different aspects of the evolution of regional labor market disparities. The choice of an appropriate approach to investigate the hypothesis of convergence depends on the characteristics of the regions under consideration.

Among the cross-sectional approaches to convergence, the concept of σ-convergence and the distributional approach are widely used to investigate the evolution of regional labor market disparities. In contrast to the economic growth literature, the concept of β-convergence only plays a minor role in the labor market context. Apart from the restricted explanatory power of this concept, an additional reason might be the strong linkage between the neoclassical growth model and the hypothesis of β-convergence.

Studies following the concept of σ-convergence in general find no evidence for a clear trend in the dispersion of regional labor market performance. Time periods where the inequality between regions becomes smaller, alternate with time periods of increasing inequality. Therefore, the majority of the results indicate persistent labor market inequalities rather than convergence or divergence of regional labor markets. This observation holds for many European countries but also for Australia and New Zealand. Only for the US does Eichengreen (1990) find a clear positive trend for the dispersion of regional unemployment rates. However, the findings by Rowthorn/Glyn (2006) suggest no clear trend in the dispersion of US regional employment rates. Thus, one could not expect that the inequality across regions would disappear over time at least in short or medium terms.

Studies following the distributional approach to convergence find less intra-distribution mobility of regions. The results indicate a persistent geographical distribution of regional labor market performance. Baddeley/Martin/Tyler (1998) find that the ranking of regions due to their unemployment rates is very stable for European countries. The studies by Martin (1997) and Gray (2004) confirm this result for the UK. The findings by Overman/Puga (2002) for Europe and Pehkonen/Tervo (1998) for Finland suggest that mobility of regions between different unemployment states is rather weak in short and medium terms. Only for the long run do Pehkonen/Tervo (1998) find a distinct increase in the transition mobility. However, Overman/Puga (2002) and Pehkonen/Tervo (1998) find that the mobile regions are in general those with a medium unemployment rate. According to Overman/Puga (2002), this form of intra-distribution mobility leads to a polarization in the geographical distribution of regional unemployment in Europe and not to more equality among the European regions.

The results of the studies testing for σ-convergence indicate that cyclical behavior strongly affects the dispersion of regional labor market performance. Because of this strong cyclical behavior, one can hardly conclude that differences in initial conditions are the only source of regional labor market disparities. Economic disturbances appear to be an important driving force for the evolution of regional labor market disparities in many countries. This aspect is not necessarily restricted to changes in the business cycle, but can also contain changes in labor demand, structural changes or technological change. The cross-sectional approach considers convergence as a catching-up process between favorable and unfavorable regions. Hence, this approach fails to account for such a development. However, the time series approach sheds light on the relationship between region-specific shocks and the evolution of regional labor market disparities. Therefore, it appears to be fruitful to follow the hypothesis of stochastic convergence when examining the evolution of regional labor market disparities.

The common way of investigating the hypothesis of stochastic convergence is to test whether the deviations of the regional variables from their national counterpart follow a stationary process. Unit roots are considered as the main reason why a time series follows a non-stationary process. Hence, unit root tests are usually applied to test the hypothesis of stochastic convergence. Another possibility is to test whether the regional labor market variables and their national counterpart are co-integrated.

In general, univariate unit root test find no evidence of stochastic convergence for regional unemployment rates. In contrast, the results for regional employment growth rates are rather mixed. The results by Blanchard/Katz (1992) for the US and Decressin/Fatás (1995) for Europe provide no evidence of stochastic convergence. The results by Jimeno/Bentolila (1998) for Spain, Debelle/Vickery (1998) for Australia, and Choy/Maré/Mawson (2002) for New Zealand favor the hypothesis of stochastic convergence.

In contrast, the findings of studies using panel unit root tests confirm the hypothesis of stochastic convergence for regional employment and regional unemployment. According to these findings, a stable long-run relationship between regional (un)employment exists. Economic disturbances do not induce divergent behavior and region-specific shocks only have transitory effects.

However, these results have to be interpreted with caution. As Bayer/Jüßen (2007) show, the panel unit tests are sensitive to the choice of the lag length to account for autocorrelation in the ADF regression for the different cross-sectional units. However, many studies do not determine the optimal lag length for each cross-sectional unit but use a homogeneous lag length for all units. Furthermore, the panel unit root tests applied in the studies under review assume that cross-sectional units are not correlated with each other. However, if such cross correlation exists, these first generation panel unit root tests tend to reject the hypothesis of a unit root too often (see, for example, O'Connell 1998 and Baltagi/Bresson/Pirotte 2007).

It is also possible to investigate the hypothesis of stochastic convergence by testing for a co-integration relationship between regional variables and their national counterpart. A number of studies exist which choose this approach to examine unemployment rates in the UK. The findings from studies following an univariate approach are rather mixed. Gray (2004) finds evidence for a cointegration relationships between regional unemployment rates in the UK in a multivariate setting. Analysis by Eichengreen (1993) indicate that a stable long-run relationship exists between regional unemployment rates and the national unemployment rate in Italy, while for regions in the US, no clear co-integration relationship is found.

2.2 Adjustment to shocks

The previous section already highlighted the role of region-specific shocks and economic disturbances as an origin of regional labor market disparities. Long-lasting region-specific shocks can cause persistent labor market disparities. This raises the question: How long does it take until things return to normal after a region-specific labor market shock?

The studies by Bayer/Jüßen (2007), Kunz (2012), and Eichengreen (1993) already reviewed in the previous section, provide results for the half-life of shocks in relative regional unemployment rates. The findings by Bayer/Jüßen (2007) and Kunz (2012) for German regions are based on the results of the panel unit root test by Levin/Lin/Chu (2002). The findings by Eichengreen (1993) for the US, the UK, and Italy are based on an error correction model.

In addition, several studies use autoregressive (AR) models to examine mean reversion behavior of labor market variables. Usually impulse response functions are derived from the results of the AR model to graphically visualize the adjustment process after a simulated shock. This approach provides insights on about how long it takes until the effects of a shock disappear and things return back to normal. However, they only consider a detail of regional dynamics after a shock because they neglect possible interactions between different labor market variables. Furthermore, they provide no information on the underlying adjustment channels after a labor market shock. For example, the regional unemployment rate might not only return back to its initial value after a shock because new jobs were created, but also because unemployed leave the region.

In their seminal paper, Blanchard/Katz (1992) introduce a fully specified model of regional labor market dynamics. This framework examines the adjustment process after an innovation in regional employment. Blanchard/Katz (1992) identify such an innovation in regional employment as a region-specific labor demand shock. They examine joint fluctuations in employment, unemployment, labor force participation, migration and wages after a labor demand shock. Their approach makes it possible to investigate short- and long-run dynamics after a region-specific shock.[9]

Shocks which are common to all regions can not cause regional labor market disparities. Only if regions are affected by a shock in a different way can this result in regional labor market disparities. To analyze the adjustment mechanism after a region-specific shock, it is necessary to isolate region-specific movements in a

9 Note, that the study by Blanchard/Katz (1992) is not the first one which examines the regional responses to an innovation in labor demand. For an overview about the previous studies dealing with this topic see Bartik (1993).

regional variable from common movements shared by all regions. For this purpose, relative regional variables have to be constructed. The next subsection provides an overview about the several procedures to construct relative regional variables discussed in the literature.

Apart from the empirical framework, Blanchard/Katz (1992) also introduced a theoretical framework to account for the features of regional labor market disparities. An augmented version of this model is discussed in section 2.2.2.

Section 2.2.3 presents the findings of studies using AR models to examine adjustment processes after a region-specific labor market shock. Section 2.2.4 introduces the empirical framework provided by Blanchard/Katz (1992) to investigate regional labor dynamics after a region-specific labor demand shock. Furthermore, the findings of studies adopting the original approach by Blanchard/Katz (1992) are presented in this section. Inflexible wages are considered as an impediment for quick adjustment processes. Section 2.2.5 reviews the studies investigating the role of wages during the adjustment process. Several authors augmented the original framework of Blanchard/Katz (1992). The findings of these studies are presented in section 2.2.6. The last section concludes.

2.2.1 Measures for relative regional variables

To capture the region-specific movements of a regional variable, it is necessary to isolate the movements in this variable shared by all regions. This problem is usually solved by the construction of so called relative regional variables (see also section 2.1.2). Therefore, such relative regional variables $\tilde{x}_i$ represent the relationship between a regional variable x_i and its aggregate system-wide or reference average counterpart $\overline{x}$. The definitions of relative regional variables differ in the assumptions about how the relationship between x_i and $\overline{x}$ is best described. The literature provides three different ways to construct relative regional variables to capture the region-specific evolution of a variable.

The first definition of relative regional variables assumes that the relationship between x_i and $\overline{x}$ is best described in terms of a linear relationship. The relative regional variable measured as differentials between x_i and $\overline{x}$ is given by:

$$\tilde{x}_i^d = x_i - \overline{x} \tag{2.28}$$

Constructing relative regional variables as the difference between the x_i and $\overline{x}$ corresponds to simply demeaning the data. Hence, this procedure removes a linear time trend in the data shared by all regions. The second definition assumes the relationship between x_i and $\overline{x}$ is best described by considering the ratio between these two variables. This leads to the following definition of a relative regional variable:

$$\tilde{x}_i^r = \frac{x_i}{\overline{x}} \tag{2.29}$$

Note, that the two definitions of relative regional variables picture movements in x_i and $\overline{x}$ in a different way. A shock which leads to an equal absolute change in x_i and $\overline{x}$ does not affect the differential but does influence the ratio. In contrast, a shock that leads to an equal relative change in x_i and $\overline{x}$, affects the differential but not the ratio of the two variables (see also section 2.1.2).

These two definitions assume that disturbances of the regional variables due to national movements are distributed symmetrically across regions. This means it is assumed that regions do not differ in their elasticity to common shocks. This assumption can be relaxed by combining the two approaches. This leads to a measure for relative regional variables which Blanchard/Katz (1992) and Decressin/Fatás (1995) call β-differences. Relative regional variables measured as β-differences can be expressed as:

$$\tilde{x}_i^{bd} = x_i - \beta_i \overline{x} \tag{2.30}$$

Hence, relative regional variables measured as β-differences are weighted differences between x_i and $\overline{x}$. This allows for the possibility that regions react differently to aggregate fluctuations.

However, the coefficient β_i in equation (2.30), is unknown and has to be estimated. This is usually done by applying a so called cyclical sensitivity model. This model was introduced by Thirlwall (1966) and Brechling (1967) to analyze the relationship between regional unemployment rates and their national counterpart. A more common form of the cyclical sensitivity model is given by the following regression:

$$x_{i,t} = \alpha_i + \beta_i \overline{x}_t + \varepsilon_{i,t} \tag{2.31}$$

where t denotes the time dimension with $t = 1, \ldots, T$. The coefficient β_i measures to which extent the regional variable is affected by the national variable. Regression (2.31) is run for each of the N regions with $i = 1, \ldots, N$ separately. Using the estimation results, one can calculate the β-difference at date t as $x_{i,t}^{bd} = x_{i,t} - \hat{\beta}\overline{x}_t$ for each region. Hence, the β-difference corresponds to the estimated constant $\hat{\alpha}_i$ and the error term $\hat{\varepsilon}_{i,t}$. This means the β-difference captures the variation of the regional variable which can not be explained by the national rate in regression (2.31).

The approach by Thirlwall (1966) and Brechling (1967) additionally provides some insights into which of the three definitions of relative regional variables is most appropriate for the underlying data. If $\hat{\beta}_i$ is equal to unity for all regions, the values of regional variables would shift perfectly parallel to the national variable and estimates only vary in the constant $\hat{\alpha}_i$. In this case, the relationship between the regional and the national variable is best described by differentials. If the estimated constants are close to zero instead, regional variables are a perfect multiple of the national variable. This indicates that the relationship is best described by ratios. Thus, if there are stable absolute differences instead of stable ratios, the estimates should vary mainly in the constants and not in the value of $\hat{\beta}_i$. If both $\hat{\alpha}_i$ and $\hat{\beta}_i$ vary between the regions, then the β-differences are the appropriate measure.

The application of simple differences are very common (see, for example, Blanchard/Katz 1992, Jimeno/Bentolila 1998, or Mäki-Arvela 2003) as well as the application of β-differences (see, for example, Decressin/Fatás 1995, Fredriksson 1999, Debelle/Vickery 1999, Choy/Maré/Mawson 2002, Pekkala/Kangasharju 2002a,b, or Kunz 2012). To the best of my knowledge, no study investigating regional labor market dynamics after a region-specific shock constructs relative regional variables using the ratio of x_i and $\bar{x}$. However, it seems noteworthy that in many cases, relative regional variables are calculated for variables measured in logarithm. Because $\log(x_i) - \log(\bar{x}) = \log(x_i / \bar{x})$, the studies implicitly focus on the ratio between a regional variable and its national counterpart and not the differential between these two measures.

Note, when examining the hypothesis of stochastic convergence it is necessary to make an assumption about the long-run relationship between the regional variables and their national counterpart (see section 2.1.2). Therefore, the results of the cyclical sensitivity model might also provide helpful information for this decision.

2.2.2 Theoretical framework

This section introduces a theoretical framework to analyze the adjustment mechanism after a labor demand shock. The model is based on Blanchard/Katz (1992) and the extensions by Jimeno/Bentolila (1998).

The model builds on the following two assumptions: Regions produce different bundles of goods that are all sold on the national market. Production takes place under constant returns to labor, and the demand of each product is downward slopping. Further, it is assumed that workers and firms are mobile across regions.

Let $w_{i,t}$ denote the logarithm of the wage in region i at time t, $n^*_{i,t}$ denotes the the logarithm of the labor force and $ur_{i,t}$ is the logarithm of the unemployment rate. The unemployment rate corresponds to the ratio of unemployment to employment. Hence, the logarithm of employment is approximately given by $n^*_{i,t} - ur_{i,t}$ (see

Blanchard/Katz 1992). Labor demand in region *i* at time *t* measured relative to its national counterpart is given by:

$$\tilde{w}_{i,t} = -d(\tilde{n}^*_{i,t} - \tilde{ur}_{i,t}) + \tilde{z}_{i,t} \tag{2.32}$$

where $\tilde{w}_{i,t}$ denotes the relative regional wage, $\tilde{n}^*_{i,t}$ denotes the relative regional labor force, $\tilde{ur}_{i,t}$ the relative regional unemployment rate and $\tilde{z}_{i,t}$ is the position of the labor demand curve.

Firms move to regions where labor costs are lower. Factors other than wages, such as, for example, public sector infrastructure, natural resources or local taxes, may also affect firms' location decisions. Hence, some regions consistently attract new firms, while other regions do not. Therefore, movements in $\tilde{z}_{i,t}$ are formalized as:

$$\tilde{z}_{i,t+1} - \tilde{z}_{i,t} = -a\tilde{w}_{i,t} + x_{di} + \varepsilon^d_{i,t+1} \tag{2.33}$$

x_{di} reflects regional amenities affecting firms' decision to locate their business someplace. Moreover, x_{di} also captures drifts in the demand for individual products. $\varepsilon^d_{i,t+1}$ represents innovation to labor demand and is assumed to follow a white noise process. As regions produce different bundles of goods, they experience different shocks to labor demand and thus experience region-specific fluctuation. Note, according to equation (2.33), unemployment does not affect firms' decision for a particular region. Higher unemployment may imply a larger pool of workers to choose from and thus makes firms more likely to locate here. But higher unemployment rates are usually associated with an unfavorable structure of the unemployed. For example, an above average fraction of long term unemployed. Further, high unemployment may be an indicator for regions in economic crisis which may lead to a lower quality of public service (see Blanchard/Katz 1992). Hence, it is assumed that firms are reluctant to locate in an area with high unemployment.

Following Jimeno/Bentolila (1998), absolute regional wages $w_{i,t}$, are assumed to depend on national wages $\bar{w}_t$ and both regional as well as national unemployment. Hence, the regional wage equation is given by:

$$w_{i,t} = f\bar{w}_t - c_A\bar{ur}_t - c_R ur_{i,t} \tag{2.34}$$

where $\bar{ur}_t$ denotes the national unemployment rate and $ur_{i,t}$ is the absolute regional unemployment rate. The response of wages to an increase in unemployment that is evenly distributed across regions corresponds to $-(c_A + c_R)$. If only regional unemployment increases while national unemployment remains constant, then regional wages decrease by c_R. Thus c_R is a measure of regional wage flexibility. The wage setting equation on the national level is given by $\bar{w}_t = -c_N \bar{u}r_t$. The wage flexibility at the national level c_N is related to $(c_A + c_R)/(1-f)$. The difference of wage flexibility at the national and the regional level is given by the dependence of regional wages on national wages and unemployment. This dependence may stem from an attempt by unions to set similar wages in all regions, or a geographically decentralized bargaining system where relative wages matter (see Jimeno/Bentolila 1998). Relative regional wages are given by:

$$\tilde{w}_{i,t} = -c_R \tilde{u}r_{i,t} \tag{2.35}$$

Higher relative regional unemployment leads to lower relative wages depending only on regional wage flexibility.

According to Blanchard/Katz (1992), it is appropriate to assume that changes in the labor force are mainly driven by migration and participation decisions and not by differences in the regions' natural population growth rate. Therefore, movements in the regional labor force are formalized as:

$$n^*_{i,t+1} - n^*_{i,t} = b_P w_{i,t} - g_P ur_{i,t} - v_{i,t+1} + b_M(w_{i,t} - \bar{w}_t) - g_M(ur_{i,t} - \bar{u}r_t) + x_{si} + \varepsilon^s_{i,t+1} \tag{2.36}$$

The first three terms on the right hand-side capture participation decisions, the remaining ones capture migration flows. It is assumed that participation depends positively on regional wage levels and negatively on regional unemployment rates. Furthermore, shocks to participation $v_{i,t}$ are assumed to affect the participation decision. Migration is assumed to depend on relative regional wages and unemployment rates. The drift term x_{si} reflects regional amenities affecting migration. $\varepsilon^s_{i,t+1}$ captures transitory movements in exogenous migration. Interregional migration only affects a region's labor force but not its national counterpart. This assumption implies that migration from foreign countries is negligible. Therefore, it is assumed that changes in the national labor force $\bar{n}^*_t$ only arise because of participation decisions:

$$\bar{n}^*_{t+1} - \bar{n}^*_t = b_p \bar{w}_t - g_P \bar{u}r_t + \bar{v}_{t+1} \tag{2.37}$$

Using equations (2.36) and (2.37) changes in the regional relative labor force are given by:

$$\tilde{n}^*_{i,t+1} - \tilde{n}^*_{i,t} = (b_P + b_M)\tilde{w}_{i,t} - (g_P + g_M)\tilde{u}r_{i,t} + \tilde{v}_{i,t+1} + x_{si} + \varepsilon^s_{i,t+1} \tag{2.38}$$

Using equations (2.32), (2.33) (2.35) and (2.38) one can solve for the paths of relative wages, relative unemployment and relative growth of the labor force:

$$\tilde{ur}_{i,t+1} = \varphi \tilde{ur}_{i,t} + \frac{d}{d+c_R}(\tilde{v}_{i,t+1} + x_{si} + \varepsilon^{s}_{i,t+1}) - \frac{1}{d+c_R}(x_{di} + \varepsilon^{d}_{i,t+1}) \tag{2.39}$$

$$\tilde{w}_{i,t+1} = \varphi \tilde{w}_{i,t} - \frac{dc_R}{d+c_R}(\tilde{v}_{i,t+1} + x_{si} + \varepsilon^{s}_{i,t+1}) + \frac{c_R}{d+c_R}(x_{di} + \varepsilon^{d}_{i,t+1}) \tag{2.40}$$

$$\begin{aligned} \tilde{n}^{*}_{i,t+1} - \tilde{n}^{*}_{i,t} = {} & \varphi(\tilde{n}^{*}_{i,t} - \tilde{n}^{*}_{i,t-1}) + \tilde{v}_{i,t+1} - \left(1 - \frac{a}{d+c_R}\right)\tilde{v}_{i,t} + \varepsilon^{s}_{i,t+1} - \left(1 - \frac{a}{d+c_R}\right)\varepsilon^{s}_{i,t} \\ & + \frac{a}{d+c_R}x_{si} + \frac{c_R(b_P + b_M) + (g_p + g_M)}{d+c_R}(x_{di} + \varepsilon^{d}_{i,t+1}) \end{aligned} \tag{2.41}$$

The speed of adjustment is determined by:

$$\varphi = 1 - \frac{dc_R(b_P + b_M) + d(g_p + g_M) + ac_R}{d+c_R} \tag{2.42}$$

Any reasonable depiction of the adjustment process suggests that φ is positive. The persistence of shocks increases with the size of φ. Note, that shocks to labor supply and labor demand have opposite implications regarding initial responses of relative wages and unemployment. An underlying positive drift x_{di} in labor demand leads to a positive relative trend in employment, higher than average wages and lower than average unemployment. An underlying positive drift in relative labor supply x_{is} leads to a positive relative trend in employment, lower than average wages and higher than average unemployment. Hence, differences in the regional amenities lead to permanent differences in growth rates.

An adverse labor demand shock increases unemployment and decreases wages. This causes a rise in net out-migration of workers and net in-migration of firms. Over time, labor and firm mobility lead to a decline in unemployment and an increase in wages until they return to normal. However, employment is permanently affected. Where the employment level ends up, depends on the speed at which workers and firms adjust to changes in wages and unemployment. But while both high unemployment and lower wages lead to labor migration, only lower wages influence a firms decision to locate. Thus, the larger the initial decline in demand is reflected in unemployment rather than wages, the larger the long-run effect of adverse employment shocks. The answer of relative wages to a labor demand shock depends on the regional wage elasticity. If the regional wage elasticity is small, adjustment mainly occurs through the migration of workers and not the creation of new jobs.

2.2.3 Autoregressive processes and impulse response analysis

Several studies examine the effects of a region-specific labor market shock in an univariate framework. To do this, they investigate the mean reversion behavior of relative regional labor market variables using autoregressive (AR) models. Let $\tilde{x}_t$ denote the relative regional variable of interest. A simple first order AR model for the relative regional variable $\tilde{x}_t$ is given by:

$$\tilde{x}_t = \alpha + \beta \tilde{x}_{t-1} + \varepsilon_t \tag{2.43}$$

The coefficient β provides information about the persistent behavior of shocks. This model can be estimated for each region separately to examine the mean reversion behavior of a particular region. However, usually the interest is not in the reaction of a certain region, but the response of the representative region to a shock. For this purpose, regions are pooled which leads to a panel AR(1) model of the following form:

$$\tilde{x}_{i,t} = \alpha_i + \beta \tilde{x}_{i,t-1} + \varepsilon_{i,t} \tag{2.44}$$

The constant α_i can be interpreted as a regional fixed effect to account for regional heterogeneity.

Blanchard/Katz (1992) specify a AR(4) model for relative regional employment growth rates covering the time period from 1952 to 1990 for US states. For unemployment, only a shorter time period is available covering the years from 1974 to 1990. Therefore, an AR(2) model is applied for relative regional unemployment rates. The pooled regression for relative regional employment growth shows that an employment shock has persistent effects on the number of employees. A one percent shock to the employment growth rate leads to a permanent increase of the employment level by 1.5 percent. This pattern can also be found for almost every of the 51 US states. For the relative unemployment rate, the pooled model indicates that five years after a shock, the effect of the shock falls to 29 percent. After ten years, the deviations between regional unemployment rates and the national unemployment rate return back to their initial values. The estimates for each state separately show that the adjustment process takes between six to ten years.

Decressin/Fatás (1995) examine adjustment processes for US States and NUTS1 regions in Europe. They run a pooled AR(2) model for relative regional employment growth rates (time period: 1966 to 1987) and relative regional unemployment rates (time period: Europe 1966 to 1987, US 1970 to 1990). Their results are in line with Blanchard/Katz (1992). A region-specific shock in employment growth has a permanent effect on the employment level. The effects appear much stronger for the US than for Europe. In addition, for the relative regional unemployment rates, it is shown that region-specific shocks are less persistent in Europe than in the US. It takes four years until the relative regional unemployment rates return back to their initial value while it takes up to ten years in the US. These results appear surprising because regional unemployment is usually considered more persistent in Europe compared to the US. However, based on the results of a pooled AR(2) model for absolute unemployment rates, Decressin/Fatás (1995) conclude that in Europe common shocks have persistent effects while region-specific shocks only have transitory effects.

Bayer/Jüßen (2007) investigate the adjustment process after a region-specific shock on regional unemployment rates for West German federal states for the time period 1960 to 2002. They use a pooled AR(1) model allowing for fixed effects. According to their results, the half-life of a shock is between five to six years. This is in line with their finding based on the test by Levin/Lin/Chu (2002) (see section 2.1.2).

Kunz (2012) specifies a pooled AR(2) model for relative regional unemployment rates of West German federal states for the time period 1989 to 2004. Additionally, results for districts are presented for the same time period. To overcome the so called Nickell bias (see Nickell 1981) of the lest square dummy variable (LSDV) estimator in a dynamic panel framework,[10] the bias-corrected LSDV estimator provided by Bruno (2005) is used for the AR(2) model. After a one deviation shock, it takes between four and five years for federal states before the relative regional unemployment rate returns back to its initial value. To compare the results to those by Decressin/Fatás (1995) for Europe, he re-estimates the AR(2) model for German federal states for the time period 1966 to 1987. The results are similar to both the findings for the time period 1989 to 2004 and the findings provided by Decressin/Fatás (1995) for Europe. The smaller districts appear to react more sensitively to a region-specific shock. It takes about seven years until a shock on relative regional unemployment rates cancels out. These results indicate that the half-life of a region-specific shock is about two to three years for federal states and districts. In both cases, the half-

10 The problem of the LSDV estimator in a dynamic panel framework is discussed in more detail in section 5.1.4.

life of a shock is longer than the predicted half-life by the test by Levin/Lin/Chu (2002) (see section 2.1.2). One reason might be that the results are sensitive to the selection of the lag structure.

Rowthorn/Glyn (2006) apply a pooled Dickey-Fuller regression corresponding to equation (2.25), to investigate the mean reversion behavior of relative regional employment rates for US states. They estimate different forms of this regression allowing for different deterministic terms such as fixed effects and trends. To account for the Nickell bias, Rowthorn/Glyn (2006) develop a bias-corrected estimator for the Dickey-Fuller regression. Their findings suggest that the adjustment process after a region-specific employment shock is only weak and sluggish. Rowthorn/Glyn (2006) argue that much of the labor market dynamics of US states found by earlier studies occurs due to measurement errors in the Census series for state level labor force variables and short time series.

2.2.4 The empirical framework by Blanchard/Katz (1992)

Regional labor market adjustment after a labor demand shock and labor market mobility are closely connected. Suppose a region is hit by a negative labor demand shock. A person who loses his or her job can either remain unemployed in his or her area of residence, exit the labor force or move to another area. Vice versa, if there is an increase in regional labor demand, the new jobs can be either filled by unemployed people, people out of the labor force or people who move into the region. Hence, changes in employment can be decomposed into changes in unemployment, changes in labor force participation and changes in population due to migration. Of course, reasons for changes in the working age population can either be triggered by natural changes or migration. Blanchard/Katz (1992) point out that the differences in employment growth across regions predominantly result from migration, rather than natural population growth. Hence, it appears appropriate to assume that changes of the population after an regional employment shock occur due to migration and to consider migration as the corresponding adjustment mechanism. Therefore, the mobility of labor between these different labor market states is the main adjustment channel after regional labor market shocks. It is also possible to derive this relationship based on the employment rate in the following way (see, for example, Rowthorn/Glyn 2006 or Fredriksson 1999):

$$\begin{aligned}\text{employment rate} &= \frac{\text{employment}}{\text{population}} \\ &= \frac{\text{labor force}}{\text{population}} \times \frac{\text{employment}}{\text{labor force}} \\ &= \frac{\text{labor force}}{\text{population}} \times \left(1 - \frac{\text{unemployment}}{\text{labor force}}\right) \\ &= \text{participation rate} \times (1 - \text{unemployment rate})\end{aligned} \tag{2.45}$$

Rearranging equation (2.45) leads to the following identity for employment:

$$\text{employment} = (1 - \text{unemployment rate}) \times \text{participation rate} \times \text{population} \tag{2.46}$$

An empirical model to analyze the adjustment dynamics after a labor market shock must be able to get a complete characterization of the flows of these different labor market states. Furthermore, possible feedback effects between these factors should be taken into account.

In their seminal paper, Blanchard/Katz (1992) suggest a vector autoregressive (VAR) model to explore the strength of these different adjustment mechanisms. The VAR is specified for the employment growth rate (γ^n), the logarithm of the labor force employment rate (*le*), which corresponds to the ratio between employment and the labor force, and the logarithm of the participation rate (*pr*). All variables enter the VAR measured as relative regional variables to trace the effects of a region-specific employment shock. The VAR takes the form:

$$\tilde{\gamma}^n_{i,t} = \alpha_{i10} + \alpha_{i11}(L)\tilde{\gamma}^n_{i,t-1} + \alpha_{i12}(L)\tilde{le}_{i,t-1} + \alpha_{i13}(L)\tilde{pr}_{i,t-1} + \varepsilon^n_{i,t} \tag{2.47}$$

$$\tilde{le}_{i,t} = \alpha_{i20} + \alpha_{i21}(L)\tilde{\gamma}^n_{i,t} + \alpha_{i22}(L)\tilde{le}_{i,t-1} + \alpha_{i23}(L)\tilde{pr}_{i,t-1} + \varepsilon^{le}_{i,t} \tag{2.48}$$

$$\tilde{pr}_{i,t} = \alpha_{i30} + \alpha_{i31}(L)\tilde{\gamma}^n_{i,t} + \alpha_{i32}(L)\tilde{le}_{i,t-1} + \alpha_{i33}(L)\tilde{pr}_{i,t-1} + \varepsilon^{pr}_{i,t} \tag{2.49}$$

where α refers to the coefficients, (*L*) denotes the lag structure and error terms are denoted by $\varepsilon^n_{i,t}$, $\varepsilon^{le}_{i,t}$ and $\varepsilon^{pr}_{i,t}$.

Because of the lag structure of the VAR, current changes in $\tilde{\gamma}^n_{i,t}$ are allowed to affect $\tilde{pr}_{i,t}$ and $\tilde{le}_{i,t}$ but not vice versa. Blanchard/Katz (1992) motivate this specification by the identification assumption that unexpected innovations in employment $\varepsilon^n_{i,t}$ reflect movements in labor demand and not movements in labor supply. Therefore, the specification of the VAR excludes the possibility of current changes in employment due to labor supply factors.

Furthermore, note that the unemployment rate does not enter the VAR model directly. According to equation (2.45), the relationship between the unemployment rate ur_i and the labor force employment rate le_i can be described so that $\log le_i = \log(1 - ur_i) \approx -ur_i$. Blanchard/Katz (1992) use this relationship to deduce the evolution of the unemployment rate from the evolution of the labor force employment rate.

Also migration does not enter the VAR as a separate variable. In this specification of the VAR, migration represents a residual variable. This means changes in employment which can neither be explained by changes in unemployment nor changes in labor force participation are attributed to changes in migration.

The VAR can be estimated separately for each region. But usually the primary concern is the response of the representative region to a region-specific labor demand shock. For this purpose, all regions are pooled together in the VAR. To allow for fixed effects, the VAR is usually augmented by region-specific constant terms in each equation.

Blanchard/Katz (1992) investigate the adjustment process after a labor demand shock for US states. Their time series covers the period 1976 to 1990. They do pooled estimation of the VAR by pooling the states within Census divisions and by pooling all US states together. This leads to a so called panel vector autoregressive (PVAR) model. For each variable in the PVAR, two lags were allowed.

The results presented in Blanchard/Katz (1992) suggest that a one period downturn of employment by one percent, leads to a permanent effect on the employment level. Four years after the labor demand shock, the employment level is two percentage points below its initial value. Afterwards, the effect of the labor demand shock diminishes. But in the long run, the employment level remains 1.3 percentage points below its initial value. In the first year, the decline in employment is reflected in a change of the unemployment rate of 0.32 percentage points and a change in the participation rate of 0.17 percentage points. After the first year, migration accounts for 52 percent of the change in regional employment because of the shock. This means that a decrease in relative regional employment by 100 workers, leads to an increase in unemployment by 30 workers and a decrease in the participation of 5 workers in the initial year. This implies that net out-migration increases by 65 workers. By five to seven years, the participation rate as well as the unemployment rate return back to their initial values. Thereafter, the response of the change in employment consists entirely of the migration of workers. These results indicate that for US states, labor mobility is the dominant adjustment mechanism.

The framework introduced by Blanchard/Katz (1992) was adopted in numerous studies. The adjustment processes after a region-specific labor demand shock was investigated by Decressin/Fatás (1995) and Tani (2003) for Europe, by Jimeno/Bentolila (1998) for Spain, by Pekkala/Kangasharju (2002a) for Finland, by Kunz

(2012) for West Germany, by Leonardi (2004) for Italy, by Montalvo (2006) for the Philippines, by Kawagoe (2004) for Japan, by Debelle/Vickery (1998) for Australia, and by Choy/Maré/Mawson (2002) for New Zealand. Note, that whereas Blanchard/Katz (1992) simulate a negative employment shock, some of the studies cited above examine the effects of a positive labor demand shock. Because the studies make the implicit assumption that negative and positive labor demand shocks operate symmetrically, the results can easily be compared.

Decressin/Fatás (1995) investigate regional labor market dynamics on the NUTS1 level in Europe and compare the results to those obtained for the US states. The time series covers the period from 1975 to 1987 for Europe and the period from 1976 to 1990 for the US. A one standard deviation shock in regional employment raises the regional employment level permanently by 1.61 percentage points in Europe and by 1.44 percentage points in the US. Note, that the results of the other studies reviewed in this section also suggest that a labor demand shock has a permanent effect on the regional employment level. The size of a typical labor demand shock is quite similar for the US and Europe. But in the long run, the effect is stronger in the US than in Europe. Further, differences arise from the contribution of participation and migration in the adjustment process. In the year of the shock, the participation rate increases by 1.20 percentage points and the unemployment rates decreases by 0.35 percentage points in Europe. In contrast, the findings suggest that in the US, the participation rate only increases by 0.26 percentage points and the unemployment rate decreases by 0.43 percentage points. In Europe, an increase in the labor force participation rate accounts for most of the rise in employment due to a labor demand shock in the first three years. Only then does migration account for a similar proportion of the change in employment as in the US.

The minor role of migration as an adjustment mechanism in Europe compared to the US might occur because people are reluctant to migrate across countries in Europe. But this does not imply that people are also reluctant to migrate within their countries. Hence, Decressin/Fatás (1995) present additional analysis for West Germany, Italy and the UK. Even on the national level, labor force participation still appears to be the main adjustment mechanism in the short run. The role of unemployment is negligible for the UK and West Germany. Migration does not react much in the first three years after the shock except in West Germany.

However, the results provided in Tani (2003) for European regions largely differ from the findings by Decressin/Fatás (1995). While Decressin/Fatás (1995) combine data from different sources, the analysis in Tani (2003) is based on data from the Eurostat's Labour Force Survey. This assures that the data builds on internationally comparable definitions and methodology. Tani (2003) presents results for a panel of 166 regions and the 51 regions used in Decressin/Fatás (1995). The time series covers the period from 1988 to 1997. For the sample of 166 regions a one percent labor demand shock reduces the unemployment rate by 0.21 percentage points and increases the participation rate by 0.32 percentage points. This means 47 percent of the response to the employment shock can be attributed to migration. For the sample of 51 regions, the contribution of migration to the adjustment process in the initial year is 54 percent and, hence, even higher and clearly exceeds the value of four percent found by Decressin/Fatás (1995). The labor demand shock has no long-lasting effects on the unemployment rate and the participation rate. For both regional samples, it only takes three or four years until both variables return back to their initial values. Tani (2003) concludes that also in Europe migration represents the most important short-run adjustment channel. European workers appear much more mobile than usually assumed. Unfortunately, because of the different time periods, it is not possible to detect whether the different findings by Decressin/Fatás (1995) and Tani (2003) result from more mobile workers in the 1990s compared to the 1980s, or the new data source. That results could be sensitive in terms of the choice of the data source is suggested by Rowthorn/Glyn (2006). They argue that due to measurement errors and biases in their employment data sample, Blanchard/Katz (1992) overestimated the role of migration in the adjustment process.

The results by Pekkala/Kangasharju (2002a) for Finland and Leonardi (2004) for Italy are in line with the findings in Decressin/Fatás (1995). For Italy, as well as for Finland, labor force participation appears to be the most important adjustment mechanism in the early stage of the shock.

Pekkala/Kangasharju (2002a) present results for eleven Finnish provinces from 1976 to 2000. In the first year of a region-specific labor demand shock, 64.8 percent of the shock is absorbed by changes in labor force participation and 27.3 percent by changes in unemployment. In the short run, migration only plays a minor role in the adjustment process but becomes more and more important in the long run. Pekkala/Kangasharju (2002a) also present results for adjustment processes on the regional level after an aggregate labor demand shock. In contrast to a region-specific labor demand shock, a nationwide labor demand shock has a long-lasting but not permanent effect on the employment level. The employment level returns back to its initial value after twelve years. Furthermore, the findings suggest that the role of the adjustment channels differs between region-specific and nationwide shocks. In the first year, more than 62.9 percent of a nationwide shock is absorbed by the unemployment rate and even ten years after the shock, the unemployment rate accounts for more than 60 percent of the response to the shock. About one third of the shock is absorbed by labor force participation. In the short run as well as in the long run, migration only plays a minor role in the adjustment process. Compared to a region-specific shock, a nationwide shock seems to have long-lasting effects on the unemployment rate and the participation rate. After a region-specific shock, it takes four years for the unemployment rate and about six to seven years for the participation rate until the effect of the shock disappears. In the case of a nationwide shock, it takes up to eleven years until the two variables reach their initial values.

Leonardi (2004) examines 20 Italian regions during 1960 to 1999. His findings are very similar to the results by Pekkala/Kangasharju (2002a). In the first year, more than 60 percent of the shock is absorbed by the participation rate and more than 30 percent by the unemployment rate. The effect of the shock on participation and unemployment is very persistent. Even after 15 years, the unemployment rate and the participation rate have not reached their initial values. Hence, migration does not appear to be a sufficient adjustment mechanism within Italy. These results are in line with the findings by Decressin/Fatás (1995) for Italy.

In contrast, Jimeno/Bentolila (1998) identify migration as the most important adjustment mechanism after a region-specific labor demand shock for Spain. Jimeno/Bentolila (1998) examine 18 regions in Spain. Their time series covers the period 1976 to 1994. In the fist year, migration already absorbs 41 percent of the shock, followed by the unemployment rate with 36 percent and the participation rate with 23 percent. As in the Italian case, the shock shows persistent effects on participation and unemployment. It takes more than 15 years until the unemployment rate and the participation rate return back to their initial values. Jimeno/Bentolila (1998) conclude that in the Spanish case, the response of participation due to a shock is small compared to Europe, and the response of migration is small compared to the US. However, unemployment bears a significant fraction of the adjustment process. In Spain it still accounts for about one third of the change in employment after three years.

Kunz (2012) also concludes that labor force participation only plays a minor role in the adjustment process after a labor demand shock for West German federal states. The time series covers the period from 1989 to 2004. In contrast to other studies, the results in Kunz (2012) suggest that in the short run, the main part of the shock is absorbed by the unemployment rate. A one standard deviation change of employment leads to an increase of the participation rate by 0.07 percent and a decrease of the unemployment rate by 0.28 percent. This means that in the initial year of the shock, the unemployment rate accounts for 52 percent of the shock, migration for 34 percent and the participation rate for 14 percent. The effect of the shock on the unemployment rate and the participation rate appears to be only transitory. Already one year after the shock, the unemployment rate reaches its initial value while it takes two years for the participation rate. The employment level permanently remains about 0.95 percent above its initial value. This means that very soon migration becomes the main adjustment mechanism. Kunz (2012) points out that it is reasonable to assume that the adjustment behavior of small regional units differs from those of larger regional units. Migration and commuting activities between neighboring regions are usually more intense between smaller regional units. In the case of larger regional units, much of these activities take place within the area under consideration. Therefore, he also analyzes labor market adjustment for the smaller regional level of districts. The results confirm this point of view. Even in the first year, migration absorbs 84 percent of a region-specific shock. The response of unemployment and participation is remarkably small in the case of districts. A one standard deviation labor demand shock increases the employment level by 1.62 percent, while the unemployment rate decreases by 0.21 percentage points and the participation rate only increases by 0.05 percentage points.

The results provided by Kawagoe (2004) for Japan are very close to the findings by Decressin/Fatás (1995) for Europe. Kawagoe (2004) examines a panel of ten regions for the time period 1986 to 2003. Labor force participation absorbs the main part of a region-specific labor demand shock. It still accounts for 20 percent of the initial shock after five years. The response of unemployment is only limited and the response of migration at early stages is smaller in Japan compared to Europe. Therefore, Kawagoe (2004) concludes that labor force participation plays a lager role and migration a smaller role in Japan compared to Europe.

Montalvo (2006) examines the adjustment processes for the Philippines. His panel contains eleven regions and quarterly data from 1992 to 2002. The VAR is estimated for each region separately. In addition, results after pooling all regions in a PVAR are presented. On average, it takes almost three years for the unemployment rate and the participation rate of a Philippine region to recover. A region-specific labor demand shock of one percent is reflected in an increase of the unemployment rate by 0.32 percentage points and a reduction in the participation rate by 0.67 percentage points. In terms of a loss of 100 jobs due to a region-specific shock, this means that in the initial quarter of the shock the number of unemployed in a region increases by 8 persons, participation decreases by 47 persons and 44 workers leave the region.

The analysis of Choy/Maré/Mawson (2002) for New Zealand is based on twelve regions. They use quarterly data that covers the period from the fourth quarter 1985 to the second quarter 2001. Similar to the US studies, already at an early stage, migration is the main adjustment mechanism. A one percent adverse shock to employment is associated with an initial increase of the unemployment rate of about 0.08 percentage points, whereas the participation rate decreases by 0.16 percentage points. This means that the working age population falls by 0.7 percent in the period of the shock. Expressed in terms of workers: A decrease of the number of employees by 100 workers leads to an increase of unemployment by 6 persons, a fall in the labor force by 22 persons and 71 former workers leave the region in the period of the shock.[11] Choy/Maré/Mawson (2002) conclude that migration appears to be the primary adjustment mechanism for New Zealand.

Debelle/Vickery (1998) provide results for Australia. Their panel consists of six regions and two territories. Quarterly data is used that covers the period from second quarter 1979 to first quarter 1997. A one percent decrease of employment leads to a decrease of the participation rate by 0.4 percentage points and an increase of the unemployment rate by 0.2 percentage points. It takes four years for the participation rate and the unemployment rate to recover. Although, the shock has a permanent effect on the employment level, most of the change of employment is later reversed. Thus, in the long run, most of the adjustment occurs via migration but the overall response of migration is rather small reaching its peek three years after the shock.

2.2.5 The role of wages in the adjustment process

The theoretical model introduced in section 2.2.2 implies that the speed of adjustment should be largely driven by the response of wages to a labor demand shock. However, movements of relative regional wages after a shock induce an ambiguous effect. For example, lower wages due to an adverse shock induce net in-migration of firms and the creation of new jobs. Lower wages and higher unemployment induce net out-migration of labor. The long-run effect on employment depends on the relative strength and speed of the two effects.

The original model by Blanchard/Katz (1992) neglects the role of wages in the adjustment process. However, to trace the response of wages after an innovation in labor demand, they estimate a two variable PVAR including relative regional employment growth and regional (real manufacturing) wage differentials. To examine the effect of wage adjustment on employment, the impulse response functions are calculated in a first step based on the results of the PVAR. In a next step, the responses are recomputed but all the coefficients of the lagged wages in the employment equation were set to zero to suppress the wage feedback. Of course, this two variable PVAR allows no conclusion about the role of a wage feedback on unemployment and participation. This would require augmenting the original model by including an additional wage equation. Blanchard/Katz (1992) justify their proceeding because a four variable PVAR would lead to too few degrees of freedom. An additional wage equation would reduce the size of the sample and introduce additional right hand side variables.

11 They do not sum to 100 because they are rounded to the nearest whole number (see Choy/Maré/Mawson 2002).

Comparing the response to employment with and without wage feedback, shows that in the first years after the shock, the responses do not differ very much. The wage feedback dampens the response of employment primarily in the long run. But this effect is relatively small. The findings by Blanchard/Katz (1992) suggest that without wage feedback, the employment level would end 1.6 percent below its initial value. The employment level remains permanently 1.2 percent below its initial value allowing for a wage feedback. Therefore, Blanchard/Katz (1992) conclude that there exists only a weak effect of wages on job migration and in-migration of firms.

A PVAR with an additional wage equation was examine by Choy/Maré/Mawson (2002) and Leonardi (2004). Also the study by Debelle/Vickery (1999) investigates the role of wages in the adjustment process for Australia. The three studies draw the same conclusion as Blanchard/Katz (1992).

Leonardi (2004) finds that an innovation in labor demand leads to small response of relative regional wages. The effect disappears after three years. He also finds that his results are in line with Blanchard/Katz (1992) and the wage feedback has only a modest effect on the response of employment.

Debelle/Vickery (1999) use a shorter time series compared to their three variable model in Debelle/Vickery (1998) presented above. It starts in the fourth quarter of 1981. Because of data availability, also two regions were excluded from the panel. A region-specific labor demand shock leads to a rise in the unemployment rate by 0.3 percent and a decrease of the participation rate by 0.4 percent. It takes between five and four years until both variables reach their initial values again. Compared to the three variable baseline model in Debelle/Vickery (1998) the findings are very similar. The long-run out-migration is slightly smaller excluding wages.

Because of data availability, also the panel for the four variable model by Choy/Maré/Mawson (2002) has a shorter time dimension. It covers the period from first quarter 1989 to first quarter 2001. Also their results suggest that compared to the three variable model, including wages does not alter the adjustment process much at all. There is only a small response of wages due to a labor demand shock. The wage feedback contributes only slightly to the adjustment process.

2.2.6 Further enhancement of the classical approach

The majority of the studies indicate that migration is the primary adjustment mechanism even in the short run. But in the VAR framework, migration is only a residual variable. Already Blanchard/Katz (1992) suppose that due to the specification of the VAR in conjunction with their data base, the response of migration after a region-specific shock could be overestimated. Gros (1996) argues that inconsistencies in the data could be the reason for the high response of migration after a region-specific labor demand shock. The findings by Rowthorn/ Glyn (2006) confirm this assumption.

Mäki-Arvela (2003) and Leonardi (2004) focus directly on the role of migration. They include migration as an additional variable into the PVAR.

The findings by Leonardi (2004) based on the PVAR including the in-migration rate (number of in-migrants in relation to the regional population), confirm the irrelevant role of migration as an adjustment mechanism for Italian regions. He further splits his sample of Italian regions into three subsamples for the North, the Center and the South of Italy. The results for the three subsamples suggest that participation is the primarily adjustment mechanism in Italy. But migration appears to be an effective adjustment mechanism in the North, while in the South and the Center strong effects on unemployment can be found.

Just as Pekkala/Kangasharju (2002a), Mäki-Arvela (2003) examines 11 Finnish regions for the time period 1976 to 1996. Migration enters the PVAR via the regional net-migration rate (number of net-migrants in relation to the regional population). His findings for the short run are very similar to the one presented in Pekkala/ Kangasharju (2002a). In the first year of the shock, the main part is absorbed by the participation rate followed by the unemployment rate. However, the adjustment process appears to be slightly weaker. According to Mäki-Arvela (2003), it takes around eight to ten years until the effect of the labor demand shock disappears and the variables return back to their initial values.[12] Therefore, according to the results presented in Mäki-Arvela (2003), and Leonardi (2004) augmenting the PVAR by migration does not alter the results much.

Fredriksson (1999) points out that the lock-in effects of active labor market policy may hinder the adjustment process and migration in particular. The study discusses the role of active labor market policy (ALMP) in the adjustment process for a panel of 24 Swedish counties. The time series covers the period from 1963 to 1993. ALMP covers job creation measures and training programs. Next to employment growth, participation and unemployment, the PVAR also includes wages and the program rate. The program rate corresponds to the ratio of program participants and the labor force. A shock has only transitory effects and it takes between three and four years until unemployment, labor force participation and program participation return back to their initial values. Migration accounts for 66 percent of the response to a region-specific shock in labor demand in the first year of the shock. Two years after the shock, the permanent change in the employment level is

12 Note, that the PVAR specified by Mäki-Arvela (2003), also includes a wage equation. However, the role of a wage feedback in the adjustment process is not examined separately.

almost completely absorbed by migration. Fredriksson (1999) concludes that labor mobility appears to be high in Sweden compared to other European countries and even the US. Furthermore, the findings suggest that response in program activity leads only to a small reduction of regular employment. Hence, the extent of ALMP to decelerate the adjustment process appears only very limited.

All studies assume that positive and negative labor demand shocks generate similar adjustment processes. There are, however, several reasons for asymmetric adjustment processes. For example, workers will accept decreasing real wages but usually not declining nominal wages. Hence, movements in real wages due to an adverse shock could be limited downward. Further, older workers who loose their jobs due to an adverse shock could choose early retirement schemes to avoid unemployment. Once they leave the labor force, they usually will not alter their participation decision after a favorable shock. Pekkala/Kangasharju (2002b) allow for the possibility that the course of the adjustment processes in terms of positive and negative region-specific shocks is asymmetric. As in Pekkala/Kangasharju (2002a), 11 Finnish regions are considered and the PVAR includes employment growth, the employment rate and the participation rate. However, the methodology introduced by Cover (1992) is applied to allow for different responses of unemployment and participation in the case of positive or negative changes in employment. Two new variables are generated that measure negative and positive changes in employment respectively. These variables enter the labor force employment rate equation and the participation rate equation of the PVAR instead of the original employment growth variable. The time series covers the period 1971 to 1997. The results by Pekkala/Kangasharju (2002b) show that the adjustment processes after negative and positive innovations in labor demand proceed surprisingly symmetric. The adjustment processes after a positive shock appears a little smoother and migration has a more delayed role in the case of a negative shock. Pekkala/Kangasharju (2002b) conclude that the effect of a change in region-specific labor demand is more or less independent of the direction of the shock.

2.2.7 When will things return to normal after a regional labor demand shock?

The univariate approaches examining regional unemployment dynamics after a region-specific shock show that the time until the relative regional unemployment rate returns back to its initial value, varies across countries. It takes up to ten years in the US, while the time horizon is about four years in Europe. Bayer/Jüßen (2007) and Kunz (2012) come to similar results for West German federal states where it takes around five years until a region-specific shock settles down. This means that economic disturbances seem to have more persistent effects on the evolution of regional unemployment disparities in the US compared to Europe. This result is somewhat surprising because the labor market in the US is usually considered as more flexible than the European labor market. However, these results are in line with the findings by Eichengreen (1993) based on an error correction model. He also finds that it takes longer in the US compared to the UK and Italy until the regional labor market equilibria is restored.

The same holds for regional employment. The effect of a region-specific shock on the regional employment growth rate appears to be much stronger in the US compared to Europe. Also the findings by Rowthorn/Glyn (2006) for regional employment rates in the US suggest that the adjustment process after a region-specific shock is only weak.

In contrast, most of the studies following the multivariate framework provided by Blanchard/Katz (1992) taking interactions between different labor market variables into account, find that it takes three to four years until the unemployment rate and the participation rate return back to their initial values after a region-specific labor demand shock. The findings by Blanchard/Katz (1992) and Decressin/Fatás (1995) for the US indicate that it takes five to seven years until the effect of an innovation in labor demand on the unemployment rate and the participation rate cancels out. Countries where a labor demand shock has persistent effects on unemployment and participation, are usually located in Europe. For example, the results by Leonardi (2004) for Italy and Jimeno/Bentolila (1998) for Spain show that even 15 years after a region-specific shock, the unemployment rate as well as the participation rate have not yet returned to their initial values. Also in the case of Finland, the adjustment of unemployment and participation appears to be rather sluggish. In contrast, Kunz (2012) finds that for West Germany, the effect of a labor demand shock on the unemployment rate and the participation rate is only of very short duration. Already one to two years after a shock, both variables reach their initial values.

The majority of the existing studies find that migration becomes a more and more important adjustment mechanism in the long run. The only exception is the case of Italy. Here, even in the long run, migration only plays a minor role. According to the findings by Leonardi (2004), the regions in southern and central Italy are responsible for this result. However, for a number of countries like New Zealand, the Philippines, Spain, Sweden and the US, already in early stages does migration account for most of the changes in employment due to a labor demand shock.

Decressin/Fatás (1995) conclude that participation is the most important adjustment channel in the short run in Europe. However, the results presented by Tani (2003) contradict the findings by Decressin/Fatás (1995). Tani (2003) identifies migration as the most important adjustment mechanism even in the short run. But also the country specific studies show mixed results. The studies by Mäki-Arvela (2003) and Pekkala/Kangasharju (2002a) for Finland confirm results by Decressin/Fatás (1995) as well as the findings by Leonardi (2004) for Italy. According to Fredriksson (1999) and Jimeno/Bentolila (1998), migration is the most important adjustment mechanism at an early stage for Sweden and Spain respectively. In contrast, Kunz (2012) finds for West German federal states, that unemployment absorbs the main part of the shock in the short run.

Studies which examine the role of wages during the adjustment process find that the effect of wages is only very modest. In general, the wage feedback does not prevent an increase in unemployment and hardly affects the response of relative regional employment. According to the theoretical model, the role of wages in the adjustment process is twofold. However, empirical analysis also fail to shed light on this issue. Blanchard/Katz (1992) conclude for the US, that the decline in wages does not trigger job-in-migration or job creation but leads to out-migration of labor. Also the findings by Choy/Maré/Mawson (2002) for New Zealand indicate that the wage feedback leads to a rise in the response of migration. In contrast, the results by Debelle/Vickery (1999) for Australia and Leonardi (2004) for Italy suggest that the effect of wage feedback on the migration dynamics is negligible. The role of the wage feedback remains something of a puzzle.

As the existing literature shows, the response of unemployment, participation and migration after a region-specific labor demand shock varies across countries. Hence, differences in the labor market institutions seem to influence the adjustment process after a region-specific shock. However, it should be kept in mind that the comparability of the existing studies is limited due to the different size of the regions under consideration. As Fredriksson (1999), Choy/Maré/Mawson (2002), and Kunz (2012) point out, it seems natural that labor mobility should play a greater role in the case of smaller regions compared to larger regions. The results by Kunz (2012) for West German federal states and West German districts are in accordance with this point of view.

Chapter 3

3 New insights into the evolution of regional unemployment disparities in Germany

Between 2005 and 2009, the number of unemployed in Germany as well as the German unemployment rate decreased by almost one third. Nevertheless, regional unemployment disparities are still present and very persistent within Germany. There are regions that have unemployment rates corresponding to full employment, whereas other regions are marked by deep labor market problems. The aim of this chapter is to answer the following questions: Are regional unemployment disparities in Germany still as pronounced as in the past? Is it reasonable to expect regional unemployment disparities in Germany to rise or to decline? Therefore, this chapter examines the evolution of regional unemployment disparities in Germany and tests the hypothesis of convergence for German regional unemployment rates.

Baddeley/Martin/Tyler (1998), Möller (1995), Bayer/Jüßen (2007), and most recently Kunz (2012) test the hypothesis of convergence for unemployment rates of West German federal states. Convergence analysis for Germany as a whole is still missing two decades after reunification. Hence, this chapter examines the evolution of regional unemployment rates for Germany as a whole including West and East Germany. Furthermore, to assure comparability with the previous studies, this chapter also focuses on federal states and additionally presents results for West Germany separately.

The literature review provided in chapter 2, shows that there are several concepts of convergence. However, they do not entail each other. The cross-sectional approach and the time series approach to convergence differ in the assumption about the origin of regional labor market disparities and in their point of view about the convergence process. The appropriate choice of a concept of convergence depends on whether regional labor markets in Germany are best described by transition dynamics, or whether the evolution of regional unemployment disparities are mainly driven by changes in the economic climate and economic disturbances. Otherwise, the results might be misleading. Martin (1997) and Gray (2004) follow the cross-sectional approach and the time series approach to convergence and provide a comprehensive picture about the evolution of regional unemployment disparities in the UK. However, such a comprehensive analysis is still missing for Germany. Hence, this chapter follows Martin (1997) and Gray (2004) and does not solely focus on one concept of convergence, but investigates different approaches to convergence.

Baddeley/Martin/Tyler (1998) follow different cross-sectional approaches to convergence. They provide results for the hypothesis of σ-convergence. Furthermore, they follow the distribution approach to convergence by investigating the degree of rank-order stability of regional unemployment rates. The time series in Baddeley/Martin/Tyler (1998) starts in the mid 1980s and already ends in mid 1990s. This chapter updates the findings by Baddeley/Martin/Tyler (1998). Moreover, it provides results for the concept of β-convergence.

In contrast to Baddeley/Martin/Tyler (1998), Möller (1995), Bayer/Jüßen (2007), and Kunz (2012) examine the hypothesis of stochastic convergence. As shown in section 2.1.2, the hypothesis of stochastic convergence can be tested by examining whether relative regional variables follow a stationary process. Section 2.2.1 discusses the three different ways provided in the literature to calculate relative regional variables (differences, ratios and β-differences). These approaches differ in the assumption about the appropriate relationship between the regional variable and its national counterpart. According to Baddeley/Martin/Tyler (1998), the assumption about the shape of the long-run relationship between the regional variable and its national counterpart is not trivial and might influence the results. However, it is not clear in which way the results are affected by this assumption and, therefore, how sensitive or robust the results are in terms of this assumption. To get an impression about this aspect, this section provides results for all three measures of relative regional unemployment rates.

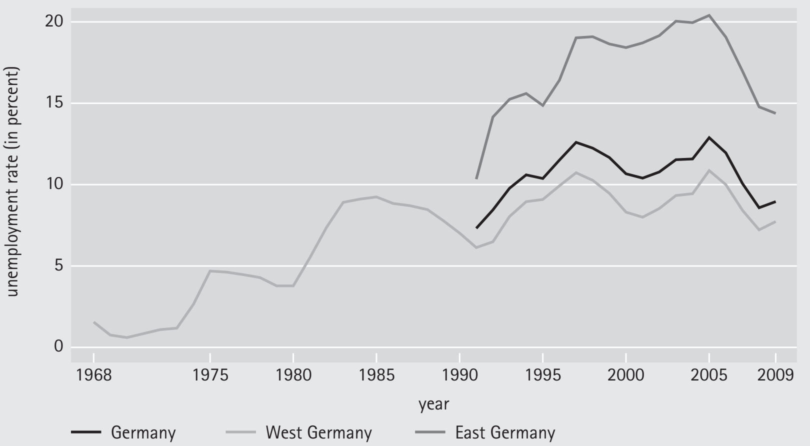
The studies cited above use first generation panel unit root tests and find evidence for the hypothesis of stochastic convergence. However, the literature shows that the results from first generation panel unit root tests might be misleading if the assumption of cross-sectional independence does not hold (see, for example, O'Connell 1998 and Baltagi/Bresson/Pirotte 2007). This chapter investigates the role of cross-sectional dependence in more detail. The tests for cross-sectional dependence provided by Pesaran (2004) and Ng (2006) show that (West) German relative regional unemployment rates exhibit cross-sectional dependence. Therefore, a second generation panel unit root test needs to be applied to test the hypothesis of stochastic convergence to take this into account. Here, the test procedure suggested by Bai/Ng (2004) is used.

The remainder of this chapter is as follows. The first section provides some stylized facts about the evolution of regional unemployment in Germany. Section 3.2 provides results for the cross-sectional approach to convergence. This section investigates the concepts of β-convergence and σ-convergence as well as the distributional approach to convergence. Section 3.4 introduces the tests for cross-sectional dependence suggested by Pesaran (2004) and Ng (2006) and provides the results of these two tests. Section 3.3 rewrites the concept of stochastic convergence in terms of regional unemployment rates. Additionally, this section investigates the relationship between regional unemployment rates and the (West) German average using the cyclical sensitivity model introduced in section 2.2.1. Section 3.5 introduces and discuses the second generation panel unit root test suggested by Bai/Ng (2004) and presents the findings of the test for the hypothesis of stochastic convergence. The final section concludes.

3.1 Trends in German regional unemployment

Data on unemployment rates of German federal states are official figures provided by the German Federal Employment Agency and measured in annual averages. Annual averaged unemployment rates are used instead of quarterly or monthly data to avoid seasonal effects. The unemployment time series for West German federal states covers the period from 1968 to 2009. The time series for East Germany starts in 1991 after German reunification and also ends in 2009. For the analysis here, two datasets were constructed. One for the West German federal states excluding Berlin and covering the period from 1968 to 2009, and one for all German federal states including both West and East Germany covering the shorter time period from 1991 to 2009.

Figure 3.1: Evolution of the German unemployment rate, 1968–2009

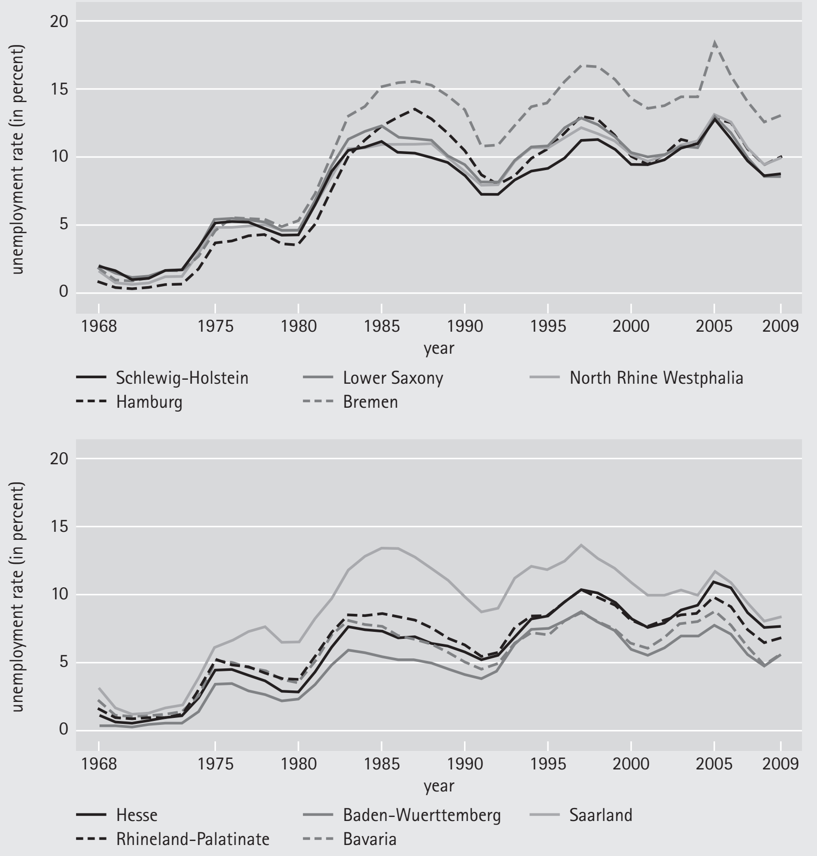


Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 3.1 reveals a number of stylized facts about the evolution of German unemployment rates. First, West German unemployment rates show an upward trend during the last four decades. The West German unemployment rate increased from 1.6 percent in 1968, to 7.8 percent in 2009. Secondly, in (East) Germany, a positive trend in unemployment is observable since 1991. Furthermore, the unemployment rate shows strong cyclical behavior. For example, the effects of the first oil crisis in 1973 and the second oil crisis in 1979 or the recession followed after German reunification in the mid 1990s can be easily identified.

From 1968 until 2005, after every slump or recession, the unemployment rate reached a new maximum. The German unemployment rate reached its highest value in 2005 with 13.0 percent. During an economic boom, the unemployment rate decreased but remained on a higher level each time compared to the previous boom. This pattern held for 40 years. However, it changed in 2007. In this year, Germany reported an unemployment rate of 10.1 percent, 0.2 percentage points lower compared to the one in 2001.

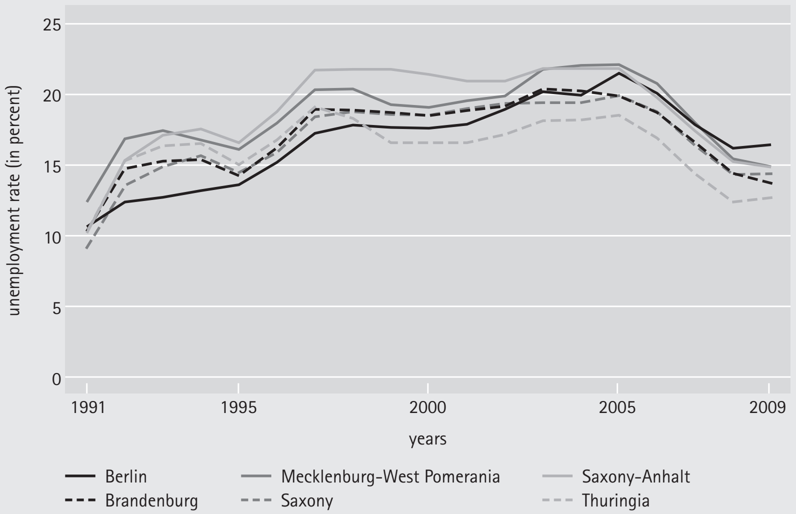
Figure 3.2: Evolution of regional unemployment rates in West Germany, 1968–2009



Source: Statistic of the German Federal Employment Agency.

Figure 3.2 and figure 3.3 show the evolution of regional unemployment rates for West German federal states and East German federal states. Regional unemployment rates are considerably higher in East Germany than in West Germany. However, figure 3.2 also shows that within West Germany, the federal states in the South perform better than those in the North.

Figure 3.3: Evolution of regional unemployment rates in East Germany, 1991–2009



Source: Statistic of the German Federal Employment Agency.

In 1968, the lowest unemployment rates can be found in Baden-Wuerttemberg (0.4 percent) and the city state of Hamburg (0.9 percent). The federal states with the highest unemployment rates were Saarland (3.1 percent), Bavaria (2.2 percent), and Lower Saxony (2.1 percent). In 2009, Bavaria was the federal state in Germany with the lowest unemployment rate (5.5 percent), followed by Baden-Wuerttemberg with 5.7 percent. The federal states with the highest unemployment rates in 2009 were all located in East Germany. They were Berlin (16.4 percent), followed by Mecklenburg-West Pomerania (14.9 percent), and Saxony-Anhalt (14.8 percent). The highest unemployment rates among the West Germany federal states in 2009 were reported by the both cities Bremen (13.1 percent) and Hamburg (10.0 percent) followed by North Rhine-Westphalia (9.9 percent).

That city states experience higher unemployment compared to the territorial states is usually considered as a common feature of the labor market. However, figure 3.2 shows that this was not always the case. In 1968, the unemployment rate of Hamburg was below the West German average. Further, Saarland, Bavaria, and Lower Saxony reported higher unemployment rates in 1968 than Bremen.

Figure 3.2 and figure 3.3 show that there has been a great similarity across the federal states in terms of the evolution of their unemployment rates, mirroring the trend and the cyclical behavior of the national unemployment rate. However, regional unemployment rates have not moved in strict unison. For example, Bavaria and Saarland were the two federal states with the highest unemployment rates in 1968. In 2009 Bavaria had the lowest unemployment rate among the German federal states and Saarland reported an unemployment rate near the West German average. In contrast to the West German federal states, the cyclical behavior of the unemployment rates of East German federal states appears to be weaker. Especially in the city state of Berlin, the trend behavior of the unemployment rate seems to mask cyclical effects.

The evolution of regional unemployment rates considered in figure 3.2 and figure 3.3 is driven by both common or national movements as well as region-specific movements. To shed more light on the region-specific evolution of regional unemployment rates, it is necessary to annihilate the common part of these absolute regional unemployment rates. Hence, relative regional unemployment rates are calculated. They should only reflect the region-specific movements of regional unemployment rates. The literature provides two simple ways to calculate relative regional unemployment rates. Let ur_i denote the regional unemployment rate and $\bar{ur}$ its national counterpart. One possibility to calculate regional unemployment rates is in terms of differentials between regional and national rate:

$$ur_i - \bar{ur} = \alpha_i \tag{3.1}$$

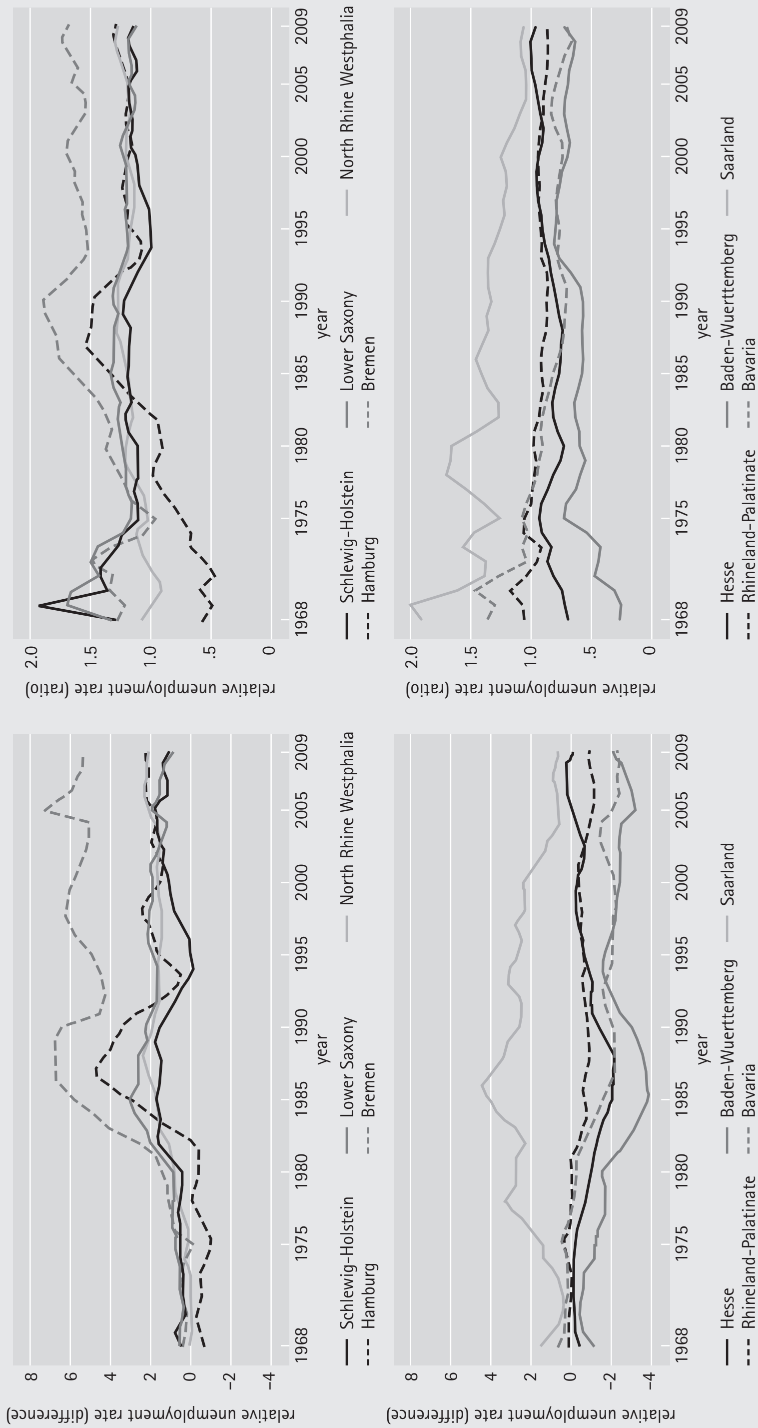
If α_i is zero, the regional unemployment rate parallels the national unemployment rate. A positive (negative) sign for the relative regional unemployment rate means that the absolute regional unemployment rate is above (below) the national average. An alternative way to define a measure for relative regional unemployment rates is in terms of the ratio between each region's rate and the average national rate:

$$\frac{ur_i}{\bar{ur}} = \beta_i \tag{3.2}$$

According to this definition, the regional unemployment rate corresponds to the national unemployment rate if β_i takes the value of one. If β_i is lower than one, the absolute regional unemployment rate is below the national average and vice versa. Furthermore, an equal absolute change in ur_i and $\bar{ur}$ does not affect α_i but β_i. In contrast, an equal relative change in the regional and the national rate affects α_i but not β_i. Therefore, using relative regional unemployment rates measured as differences or ratios, might lead to different pictures for region-specific movements of regional unemployment rates.

Figure 3.4 shows the relationship between regional unemployment rates and the West German unemployment rates over time. Indeed, until the 1990s, the evolution of relative regional unemployment rates measured as differentials and ratios shows clear differences.

Figure 3.4: Relative West German regional unemployment rates, 1968–2009



Source: Statistic of the German Federal Employment Agency, own calculations.

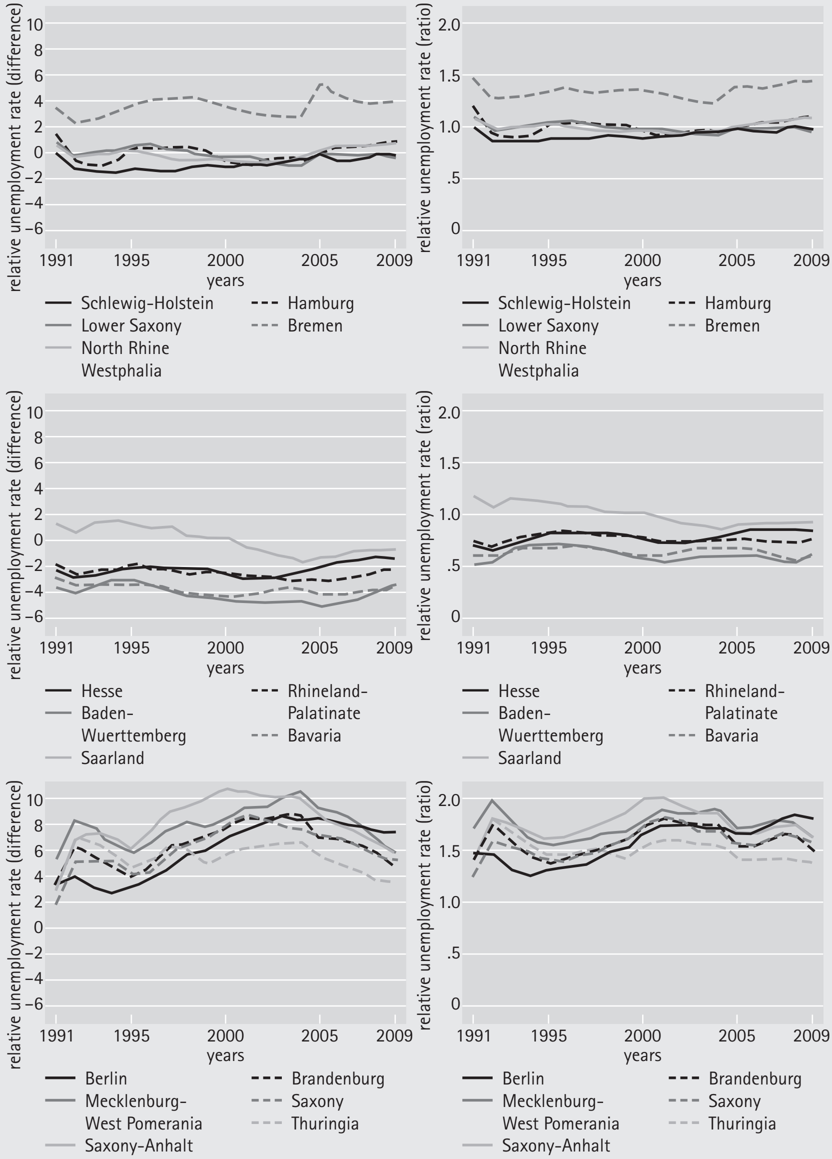
In the late 1960s and the 1970s, the unemployment rate was very low in West Germany. Therefore, also relative regional unemployment rate differentials were low. However, the results for ratios between regional unemployment rates and the West German unemployment rate indicate that there were notable relative differences between the West German unemployment rate and the unemployment rates in the federal states during this period. Until the early 1980s, there is only little movement in relative regional differentials. The exceptions are Baden-Wuerttemberg and Saarland. In contrast, much more movement is observable for relative regional ratios. For most of the West German federal states, the relative difference between regional unemployment rates and the West German unemployment rate decreased. Hence, the development of regional unemployment rates and the West German unemployment rate until the 1980s was characterized by similar absolute changes rather than similar relative changes. From the 1990s until the end of the observation period, the development of the two measures for relative regional unemployment rates was very similar.

Regional unemployment rates share trend and cyclical behavior with the West German unemployment rate. However, figure 3.4 shows that next to such common movements, also region-specific movements affect the evolution of regional unemployment rates. For example, both measures indicate an acceleration of unemployment growth compared to the West German average for the city states of Hamburg and Bremen in the early 1980s. The relative regional unemployment rate for Bremen permanently remained on a higher level compared to the 1970s. In contrast, for Hamburg, the increase of the relative regional unemployment rate appears to be only temporary. From 1987 to 1993, a decline of the relative regional unemployment rate is observable. However, Hamburg was never again able to report a below average unemployment rate as in the beginning of the observation period. Bavaria and Rhineland-Palatinate are characterized by decreasing relative regional unemployment rates. A similar pattern was observable for Saarland since the mid 1980s. This means that these federal states performed better than the West German average.

For almost every year from 1968 to 2009, Baden-Wuerttemberg reported the lowest unemployment rate among the West German federal states. In 1994 it was the first time since 1968 that Baden-Wuerttemberg lost its top position and Bavaria reported the lowest unemployment rate across the federal states for some years. The development of relative regional unemployment rates for Baden-Wuerttemberg shows a clear upward trend in the case of relative regional ratios since 1990, and for relative regional differentials already since the end of the 1980s. Also a slight upward trend for Bavaria's relative regional unemployment rate is observable during this time period. This means that around 1990, Baden-Wuerttemberg as well as

Bavaria started to perform below average compared to the West German average. Therefore, Bavaria was only able to displace Baden-Wuerttemberg as the federal state with the lowest unemployment rate in 1994 because the development of the unemployment rate in Bavaria was less unfavorable than in Baden-Wuerttemberg compared to the West German average.

Figure 3.5: Relative German regional unemployment rates, 1991–2009



Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 3.5 provides information about the evolution of relative regional unemployment rate differentials and ratios for all German federal states. For the time period under consideration, the development of relative regional unemployment rate differentials and relative regional unemployment rate ratios is similar. These results correspond to the findings for West Germany for the same time period. Region-specific movements appear to be less pronounced during this period especially in the northern federal states. For most of the West German federal states, relative regional unemployment rates show no clear tendency to diverge and remained on a stable level. One exception is Saarland. However, the difference of the relative regional unemployment rate of Saarland and the other federal states in the southern part of Germany tend to narrow. In contrast, relative regional unemployment rates in East German federal states show a positive trend from the mid 1990s until the early 2000s. This means that during this period, the differences between the East German federal states and the German average tend to widen. From then on, this trend dissipates and East German relative regional unemployment rates seem to remain on a stable level, too.

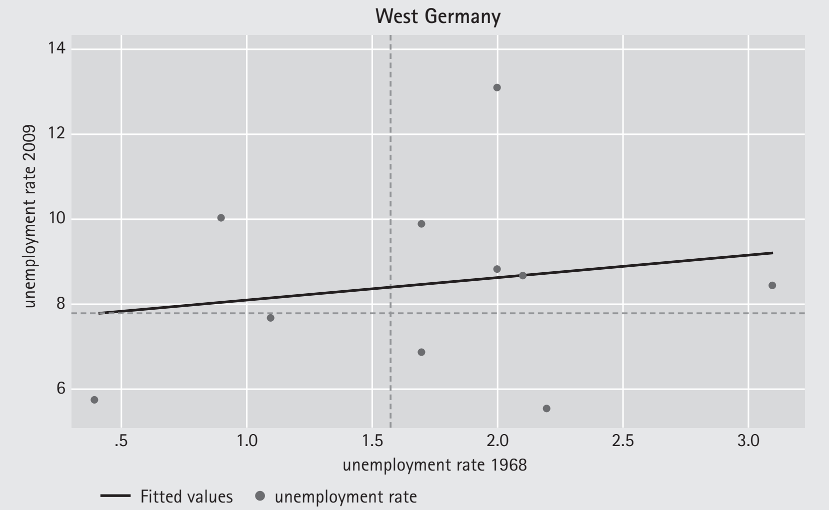
Compared to the West German federal states, relative regional unemployment rates for East German federal states show more pronounced cyclical behavior. Note, that relative regional unemployment rates represent the relationship between regional unemployment rates and the national unemployment rate. Hence, this cyclical pattern for relative regional unemployment rates indicates that absolute regional unemployment rates in East Germany react less sensitively to common changes of the economic climate than the German average. This pattern can also be observed during the last crisis. Between 2008 and 2009, most of the East German federal states report a decline in relative regional unemployment rates. In contrast, relative regional unemployment rates for Bavaria and Baden-Wuerttemberg, the two federal states with the lowest absolute unemployment rates and a strong economy, show a clear increase between 2008 and 2009. Hence, these two federal states were affected above average by the latest economic crisis.

3.2 The evolution of regional unemployment disparities

It is possible to get a first impression of the persistence of regional unemployment disparities by looking at the correlation between the unemployment rates at different points in time. In figure 3.6, the unemployment rate of West German federal states in 1968 and 2009 are plotted against each other. The dashed lines denote the West German unemployment rates in 1968 and 2009. These lines divide figure 3.6 into four panels. In the upper right panel are regions with an above average unemployment rate in 1968 and an above average unemployment rate in

2009. In the bottom left panel are regions with a below average unemployment rate in 1968 and a below average unemployment rate in 2009. The other two panels contain the regions that changed between the group of regions with an above unemployment rate and the group of regions with a below average unemployment rate over time. In the upper left panel are regions with a below average unemployment rate in 1968 and an above average unemployment rate in 2009. In the bottom right panel regions can be found with an above average unemployment rate in 1968 and a below average unemployment rate in 2009.

Figure 3.6: Persistence of West German regional unemployment rates, 1968–2009



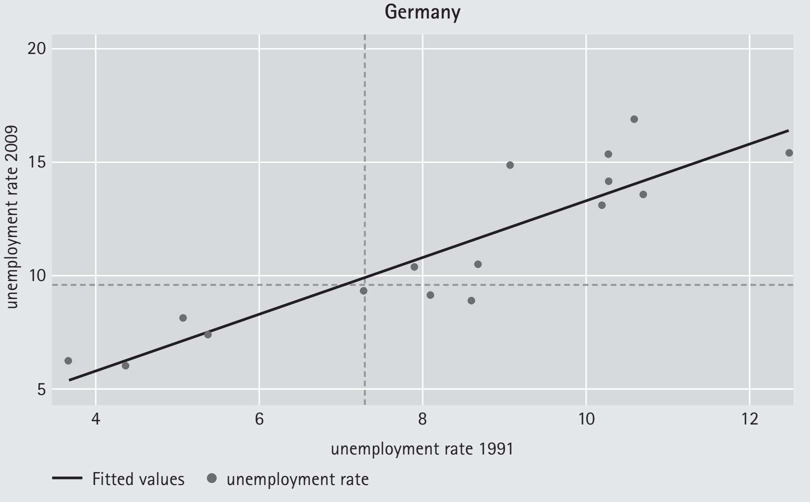
Notes: The regression line has a slope of 0.54 (*t*-stat.: 0.53, R^2 = 0.03) and the correlation coefficient is 0.18.
Source: Statistic of the German Federal Employment Agency, own calculations.

For the time period 1968 to 2009, the ranking of the West German federal states according to their unemployment rate appears to be rather weak. The regression line has a slope of 0.54 and the coefficient is not significant. The correlation coefficient of regional unemployment rates in 1968 and 2009 with 0.18 is very low. These results indicate that there is no strong linear relationship between regional unemployment rates in 1968 and 2009. A low unemployment rate compared to the other regions in 1968 does not imply that those federal states also report low unemployment rates in 2009 and vice versa. Therefore, regional unemployment rates in West Germany appear to be characterized by a certain degree of intra-distributional dynamics during the last four decades.

Further, figure 3.6 shows that during the last 40 years, three out of the ten West German federal states changed groups. The federal state in the upper left panel with a below average unemployment rate in 1968 and an above unemployment rate in

2009 was the city state of Hamburg. In 1968, Hamburg reported the second lowest unemployment rate among the West German federal states, while in 2009 the second highest unemployment rate could be found in Hamburg. Two federal states (Rhineland-Palatinate and Bavaria) reported an above average unemployment rate in 1968, and a below average rate in 2009.

Figure 3.7: Persistence of German regional unemployment rates, 1991–2009



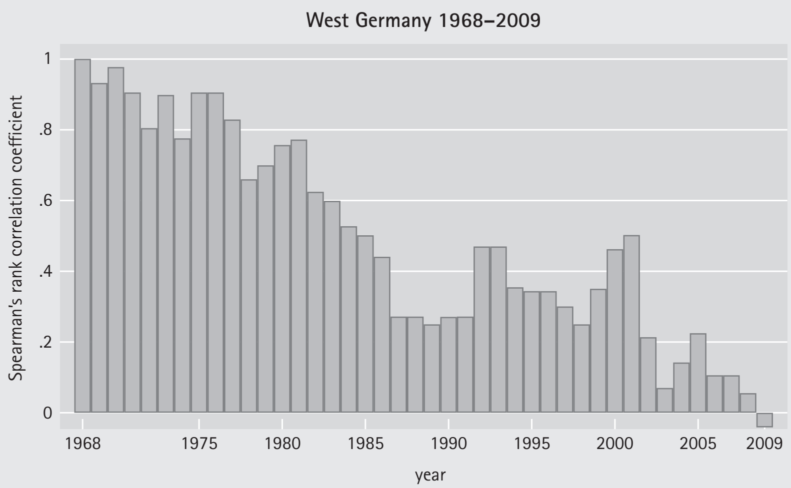
Notes: The regression line has a slope of 1.26 (t-stat.: 8.04, R^2 = 0.82) and the correlation coefficient is 0.91.
Source: Statistic of the German Federal Employment Agency, own calculations.

In figure 3.7, the unemployment rates of German federal states in 1991 and 2009 are plotted against each other. In contrast to the picture in figure 3.6, the ranking of all German federal states according to their unemployment rates has remained remarkably stable between the last twenty years. The regression line has a slope of 1.3 and a R^2 of 0.82. The correlation coefficient is very high with 0.91. Most of the federal states with an above average unemployment rate in 1991 still have an above average rate in 2009 and vice versa. Only two of the sixteen federal states under consideration changed their position compared to the German average between 1991 and 2009. Lower Saxony and Saarland reported an above average unemployment rate in 1991, and a below average unemployment rate in 2009.

Figure 3.7 indicates that between 1991 and 2009, Germany was characterized by weak intra-distributional dynamics. This finding does not seem to be solely the result of the inclusion of the East German federal states. Compared to figure 3.6, the West German federal states also appear to be grouped much closer around the regression line in figure 3.7. Therefore, a high degree of intra-distributional dynamics for the West German federal states seems to be predominantly a feature of the period before 1990.

Figure 3.7 and 3.6 give a hint on whether there is some form of intra-distributional mobility. However, comparing the relationship between regional unemployment rates at two points in time provides no information about the evolution of the regional distribution of unemployment rates over time and, hence, on periods mainly characterized by a high degree of intra-distributional dynamics. Therefore, the rank-order stability of regions according to their unemployment rates is examined. The Spearman's rank correlation coefficient considers the correlation between the rank order of regional unemployment rates in a given year and the corresponding rank order in later years.

Figure 3.8: Rank-order stability of West German regional unemployment rates, 1968–2009

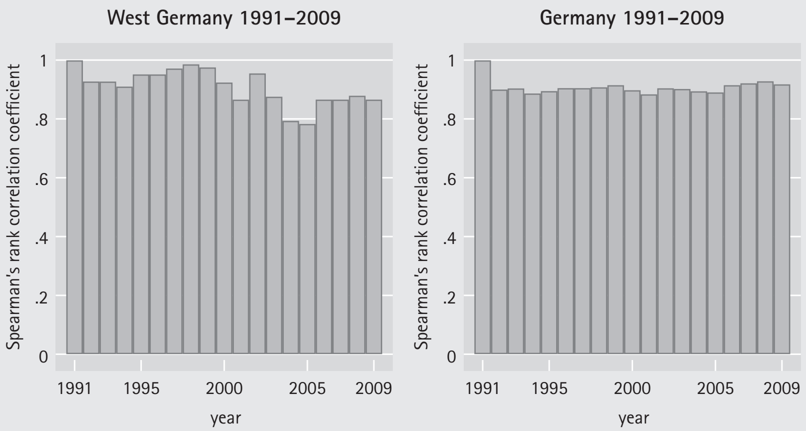


Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 3.8 presents for West Germany the development of the rank order correlation between 1968 and 2009 with 1968 as the reference year. The results clearly show a disappearance of rank-order stability during the last 40 years. This was, however, not a continuous process. Between 1968 and 1977, the rank order was stable with a rank correlation coefficient fluctuating between 0.77 and 0.98. From 1977 to 1978, the correlation coefficient fell from 0.83 to 0.66. In the following three years, the correlation coefficient increased again and reached the value of 0.77 in 1981. For the 1980s, rank-order stability shows a strong decline and the correlation coefficient was only 0.25 in 1989. Since the early 1980s, there is no evidence of dependence of the rank order in 1968, and the rank order in the current year. A *t*-test is no longer able to reject the null hypothesis of independent rank order correlation coefficients on the five percent level. During the 1990s, a clear trend is no longer observable. Since 2001, once more a decline of the rank correlation is observable, and for 2009, a negative rank correlation coefficient is reported.

These findings show that after the second oil crisis hit the labor market, a considerable change of the regional distribution of unemployment took place within West Germany. Intra-distributional dynamics of regional unemployment rates appear to be a feature of the 1980s for West Germany only. Panel 1 of figure 3.9 shows the development of the rank order correlation coefficient for West Germany during the last two decades, with 1991 as the reference year. Compared to the 1970s and the 1980s, the rank-order stability for West German federal states appears to be very persistent since reunification. During the last 19 years, the rank order correlation coefficient never fell below 0.78. These results confirm that especially the 1980s are characterized by a strong degree of intra-distributional dynamics.

Figure 3.9: Rank-order stability of regional unemployment rates, 1991–2009



Source: Statistic of the German Federal Employment Agency, own calculations.

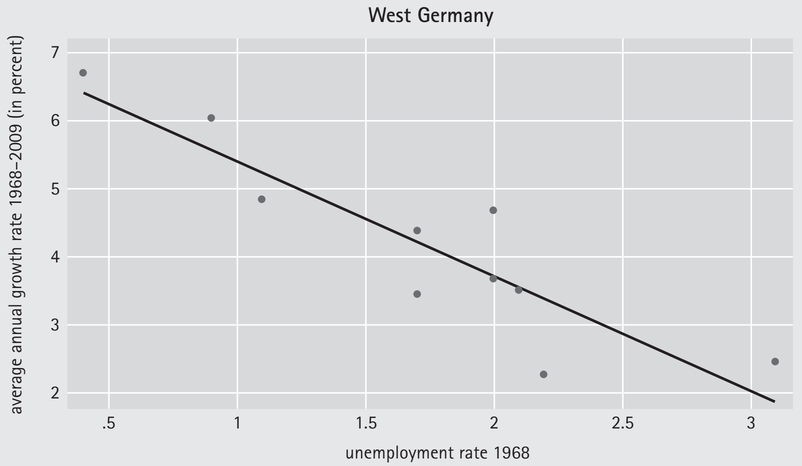
Panel 2 of figure 3.9 shows that the stability of the rank order position of all German federal states according to their unemployment rates is also striking. Between 1991 and 2009, Spearman's rank order correlation coefficient hardly changed. The correlation coefficient never fell below 0.89 during this period. Hence, rank order correlation appears to be more stable after the East German federal states are included. One reason might be the persistent higher unemployment rates in the eastern part of Germany.

However, Baddeley/Martin/Tyler (1998) point out that there is no definite relationship between intra-distributional dynamics of regional unemployment rates, and the evolution of regional inequality in unemployment. On the one hand, the strong degree of intra-distributional dynamics during the 1980s does not necessarily result in decreasing inequality of regional unemployment rates across West Germany. On the other hand, the period between 1991 and 2009 is characterized by a strong degree of rank-order stability that might be consistent with marked changes in the dispersion of regional unemployment rates. If the differences between the ranks widen or narrow over time, convergence as well as divergence can be accompanied with a strong degree of rank-order stability.

A necessary (but not sufficient) condition that German regional unemployment rates become more similar over time is the existence of some form of catching-up process. Federal states with high unemployment rates should exhibit smaller unemployment rate growth rates compared to states with low unemployment rates. Thus, the unemployment rate should sink faster in regions with high unemployment rates compared to regions with low unemployment rates. According to the concept of β-convergence, such a catching-up process requires that there is a negative relationship between the initial level of the regions' unemployment rates and their corresponding growth rates.

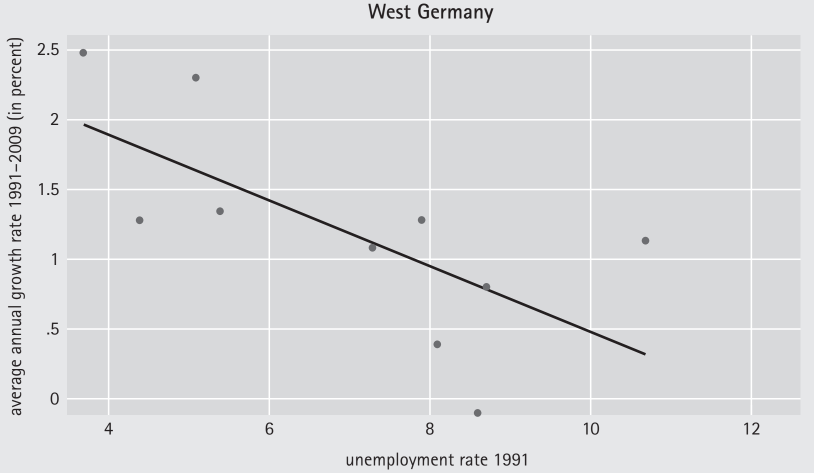
Figure 3.10 plots the unemployment rates of West German federal states against the average annual growth rate of the unemployment rates between 1968 and 2009. A negative relationship between these two measures is clearly observable. The regression line has a slope of -1.68 and a R^2 of 0.80. These results can be interpreted as evidence for the existence of unconditional β-convergence.

Figure 3.10: Relationship between West German regional unemployment rates in 1968 and their average annual growth rate 1968–2009



Notes: The regression line has a slope of -1.68 (t-stat.: -5.72, R^2 = 0.80).
Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 3.11: Relationship between West German regional unemployment rates in 1991 and their average annual growth rate 1991–2009



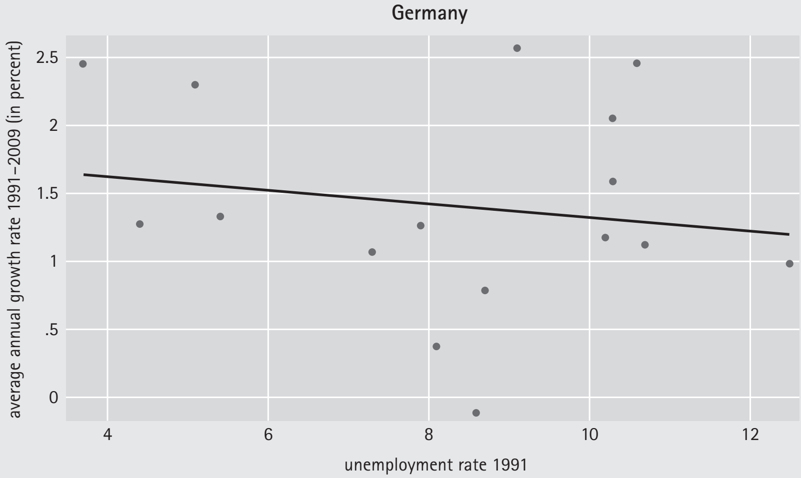
Notes: The regression line has a slope of -1.13 (t-stat.: -22.45, R^2 = 0.68).
Source: Statistic of the German Federal Employment Agency, own calculations.

Investigating the time period 1991 to 2009 for West Germany, leads to similar results that point out the existence of β-convergence (see figure 3.11). The slope of the regression line (-1.13) as well as the R^2 (0.68) is smaller compared to the period 1968 to 2009. Hence, the speed of convergence appears to be weaker during the last 20 years compared to the period 1968 to 2009. Furthermore, the findings for the last 19 years confirm that β-convergence and intra-distributional dynamics might exist independently of each other.

Figure 3.12 shows that this clear negative relationship between the initial value of the unemployment rate in 1991 and its average annual growth rate diminishes once the East German federal states are included in the regression. The regression line still has a negative slope. However, the regression coefficient with -0.05 is only small and no longer statistically significant different from zero.

Although, a clear negative relation was found for regional unemployment rates in West Germany and their average annual growth rates, there is no evidence of β-convergence considering all German federal states. Unemployment rates in East Germany are higher than in West Germany. In addition, the gap between regional unemployment rates in East Germany and regional unemployment rates West Germany is persistent. However, at the same time, the results do not support the notion that the unemployment rates in West and East Germany are being driven apart.

Figure 3.12: Relationship between German regional unemployment rates in 1991 and their average annual growth rate 1991–2009



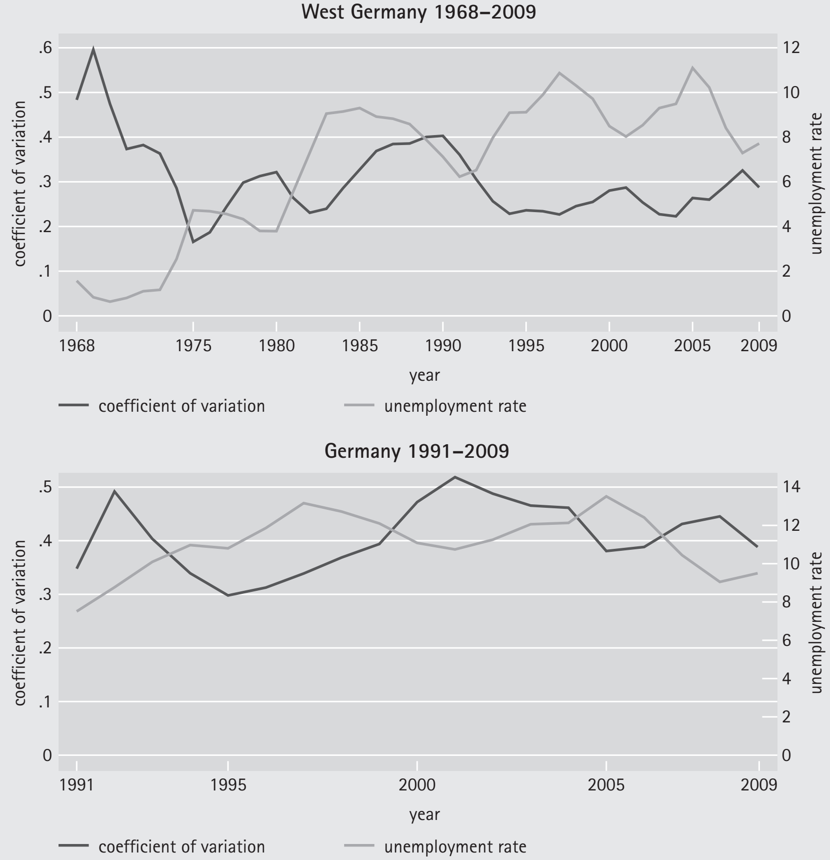
Notes: The regression line has a slope of -0.04 (t-stat.: 0.62, R^2 = 0.03).
Source: Statistic of the German Federal Employment Agency, own calculations.

The existence of β-convergence is a necessary but no a sufficient condition for the inequality across regions to decrease. Hence, it is not possible to conclude that the evolution of regional unemployment disparities in West Germany during the last 40 years is actually characterized by some form of catching-up process between favorable and unfavorable regions.

Only the concept of σ-convergence provides information on whether the negative relationship between regional unemployment rates and their growth rates triggers a catching-up process that is able to reduce the inequality across regions, leading to (more) similar unemployment rates. To examine the evolution of regional dispersion, the coefficient of variation is applied as an inequality measure. Unemployment rates in (West) Germany are up to five times higher in 2009 than in 1968. To take this steady increase of regional unemployment rates into account, a relative measure for the dispersion seems more appropriate than an absolute measure such as the standard deviation (see also the discussion in section 2.1.1).

Panel 1 of figure 3.13 shows for West German federal states that the coefficient of variation in 1968 was clearly higher than in 2009. Further, in 1991, a higher coefficient of variation was reported compared to 2009. These findings are in line with the definition of σ-convergence according to equation (2.15). However, figure 3.13 shows that the coefficient of variation did not follow a steady downward path over time. Between 1968 and 1991, periods of decreasing inequality are observable as well as periods of increasing inequality. Hence, the development of the coefficient of variation does not indicate for an unambiguous convergent or divergent behavior of regional unemployment rates during the observation period.

Figure 3.13: Dispersion of regional unemployment rates



Source: Statistic of the German Federal Employment Agency, own calculations.

From its highest peak in 1970, the dispersion of regional unemployment rates decreased until the mid seventies. From then on, the coefficient of variation increased until 1990. This means that the increase in intra-distributional dynamics during the 1980s identified by the test for rank-order stability is accompanied by an increase of regional inequality. Regional unemployment disparities widen during this period. After 1990, no clear trend for the coefficient of variation is observable. However, it seems that the amplitude of the coefficient of variation became smaller after the year 2000.

Panel 2 of figure 3.13 shows the evolution of the dispersion of regional unemployment rates for Germany. The coefficient of variation takes a higher value in

2009 compared to 1991. However, again this measure of inequality does not follow a clear trend regarding convergence or divergence of regional unemployment rates.

Baddeley/Martin/Tyler (1998) reported a cyclical rise and fall in the dispersion of West German regional unemployment rates. Figure 3.13 confirms this feature. The coefficient of variation tends to vary directly with the movements in the (West) German unemployment rate. Usually, the dispersion increases (decreases) if the national unemployment rate decreases (increases). This means that if the economic climate is positive, regional labor market disparities increase and they decrease during economic slumps. Therefore, regions that already have below average unemployment rates are the ones primarily benefiting from economic booms. In these federal states, the unemployment rate declines stronger than in federal states with high unemployment rates. However, during an economic slump, the unemployment rates of these federal states increase above average. Nevertheless, the unemployment rates of these federal states remain on a below average level. For example, Baden-Wuerttemberg and Bavaria, the two Federal States with the lowest unemployment rates, experienced the highest unemployment growth rates during the latest economic crisis.

These findings imply that even during an economic boom, it is not possible for regions with high unemployment rates to reduce them to an extent that the differences to the regions with low unemployment rates diminishes. On the contrary, a positive economic climate deepens regional labor market disparities while an economic slump leads to more similar regional unemployment rates.

Furthermore, these findings for Germany confirm that solely comparing the degree of inequality between two points in time can easily lead to erroneous conclusions about convergent or divergent behavior of regional unemployment rates. Figure 3.13 shows that observing convergence or divergence of regional unemployment rates strongly depends on where the two points in time are located. Compared to 1975, the year the coefficient of variation reached its lowest value, every other year is characterized by a higher degree of inequality. In contrast, compared to 1970, every other year is characterized by a smaller degree of inequality. Because σ-convergence implies β-convergence, this aspect additionally affects whether evidence of β-convergence is observable or not (see also the discussion in section 2.1.1).

Focusing on the cross-sectional dimension of regional labor market disparities, one neither finds evidence for convergence nor for divergence. A high degree of intra-distributional dynamics is observable for the 1980s, while the geographical distribution of regional unemployment rates appears to be very persistent during the last twenty years. Evidence confirms the existence of β-convergence for West Germany but not for Germany as a whole. However, even for West Germany,

β-convergence of regional unemployment rates did not trigger a catching-up process nor a steady decrease of regional inequality. Times of increasing dispersion alternate with times of decreasing dispersion. Economic disturbances in particular appear to be an important driving force for the evolution of regional inequality. Furthermore, the development of the distribution of regional unemployment rates as well as the dispersion of regional unemployment rates during the last two decades makes it hard to conclude that the evolution of regional unemployment disparities can be best described by a transition process. Region-specific shocks caused by economic disturbances as the main driving force of the evolution of regional unemployment disparities seem to be more in line with these findings. The time series approach to convergence can shed more light on this aspect.

3.3 The definition of stochastic convergence

Let $ur_{i,t}$ denote the unemployment rate of region i at time t with i = 1, ..., N. Further, let $\bar{u}r_t$ denote the national unemployment rate at time t. The definition of stochastic convergence according to equation (2.18) can be rewritten for regional unemployment rates as:

$$\lim_{t \Rightarrow \infty} E(ur_{i,t} - \bar{u}r_t) = \mu_i \tag{3.3}$$

In the case of stochastic convergence, the deviations of regional unemployment rates from the national unemployment rate follow a stationary process and there is a stable relationship between these two variables in the long run.

Definition (3.3) implicitly assumes that the shape of this equilibrium relationship between the regional unemployment rate and its national counterpart is linear. However, Martin (1997) points out that alternative assumptions can also be made about the shape of the equilibrium relationship between these two measures. Apart from the assumption of stable equilibrium differentials $(ur_i - \bar{u}r)$, the equilibrium relationship between these two variables could also be characterized by a stable ratio $(ur_i / \bar{u}r)$. According to Baddeley/Martin/Tyler (1998), constant differentials would imply that in equilibrium unemployment rates change by the same absolute amount across regions. In contrast, constant ratios would imply that in equilibrium unemployment rates change by the same proportion (see also section 2.2.1).

Section 3.1 shows that there are periods where the development of regional unemployment rates and the (West) German unemployment rate was characterized by similar absolute changes as well as periods where it was characterized by similar relative changes. This can be taken into account by relaxing the assumption of either stable differentials or stable ratios and combining these two assumptions:

$$ur_i = \alpha_i + \beta_i \overline{ur} \qquad (3.4)$$

If β_i is equal to unity, the regional unemployment rate would parallel the average unemployment rate perfectly. In this case, equation (3.4) can be rewritten as $\alpha_i = ur_i - \overline{ur}$ which corresponds to constant differentials in equilibrium. If α_i is zero instead, regional rates are a perfect proportion of the national rate. In this case, equation (3.4) can be rewritten as $\beta_i = ur_i / \overline{ur}$ which corresponds to stable ratios in equilibrium. Combining the assumptions of stable ratios and stable differences leads to the assumption of stable weighted differentials in equilibrium ($ur_i - \beta_i \overline{ur}$). In the literature this measure is usually called β-differences (see, for example, Decressin/Fatas 1995 and section 2.2.1).

Depending on the assumption about the shape of the equilibrium relationship, the hypothesis of stochastic convergence can be tested by examining whether regional unemployment differentials, regional unemployment ratios or regional unemployment β-differences follow a stationary process. Hence, the test procedure for the hypothesis of stochastic convergence corresponds to a test for stationarity of relative regional unemployment rates.

However, making assumptions about the equilibrium relationship between the regional unemployment rates and the national unemployment rate is not trivial. It directly affects the hypothesis of stochastic convergence to be tested. Nevertheless, the existing literature about convergence of regional (un)employment disparities usually does not deal with this subject. Therefore, we do not known how stable the results are from the tests of the hypotheses of stochastic convergence for different assumptions about the equilibrium relationship. To get an impression about this aspect, this chapter provides results for all three assumptions about the shape of the equilibrium relationship.

Of course, using β-differences appears to be a promising alternative to minimize the problem of inadequate assumptions about the shape of the equilibrium relationship because it is a combination of stable ratios and stable differences. However, while relative regional differentials and relative regional ratios are easy to calculate, equation (3.4) contains the two unknown parameters α_i and β_i. Calculating the β-differences requires consistent estimation of these parameters.

The cyclical sensitivity model can be applied to get an impression about which is the most appropriate assumption regarding the shape of the equilibrium relationship for the underlying data as well as to calculate the β-differences. This approach was introduced by Thirlwall (1966) and Brechling (1967) to analyze the cyclical behavior of regional unemployment rates. The cyclical sensitivity model is based on a regression of the following form (see also section 2.2.1):

$$ur_{i,t} = \alpha_i + \beta_i \bar{u}r_t + \varepsilon_{i,t} \tag{3.5}$$

Regression (3.5) is estimated for each region *i* with *i* = 1 … *N* separately. The coefficient β_i measures to which extent the regional rate is affected by the national rate. If β_i is equal to unity for all regions and estimates only vary in the constant α_i, the relationship between the regional unemployment rates and the national unemployment rate would be best described by stable differences. If the estimated constants are close to zero instead and β_i differs from unity, this would correspond to stable ratios. If α_i differs from zero and β_i differs from unity, then the relationship between the regional unemployment rates and the national unemployment rate is best described by a combination of the two assumptions. The *β*-differences for each region *i* at date *t* can be calculated as $ur_{i,t} - \hat{\beta}_i \bar{u}r_t$. This means that this measure corresponds to the sum of the estimated constant $\hat{\alpha}_i$ and the error term $\hat{\varepsilon}_{i,t}$.

A regression of the form of equation (3.5) was estimated for each federal state separately with the regional unemployment rate as the endogenous and the (West) German unemployment rate as the exogenous variable. For all German federal states and the time period 1991 to 2009, the *t*-test against the null hypothesis of the constant being equal to zero is only rejected on the five percent level for Hesse and Bavaria. The hypothesis of $\hat{\beta}_i$ being equal to unity is rejected for nine of the sixteen federal states (Bremen, Rhineland-Palatinate, Baden-Wuerttemberg, Bavaria, Brandenburg, Brandenburg, Mecklenburg-West Pomerania, Saxony, Saxony-Anhalt and Thuringia) on the five percent level. The estimates mainly differ with respect to the regression coefficient β_i. Therefore, the relationship between the regional and the German unemployment rate appears to be best characterized by stable ratios.

For the West German Federal States and the time period 1968 to 2009, the hypothesis of α_i being zero is rejected on the five percent level for six of the ten West German federal states (Hamburg, Bremen, Rhineland-Palatinate, Baden-Wuerttemberg, Bavaria and Saarland). The hypothesis of β_i being equal unity is rejected on the five percent level for all West German Federal States except Hesse. In the case of West Germany, the estimates mainly differ in β_i which is not in line with the assumption of stable differences. Therefore, the shape of the relationship between regional unemployment rates and the national unemployment rate appears to be best described by ratios. However, *β*-differences might also be an appropriate measure because of the mixed results for α_i.

The results for the West German federal states as well as for all German federal states show that a certain measure for the relationship between regional unemployment rates and their national counterpart is suitable for the majority of the federal states, but not for all federal states. Up to a certain degree, assumptions about the shape of the equilibrium relationship always seem to be a compromise.

The estimation results of the cyclical sensitivity model show some critical properties of the β-differences. The highest values for the regression coefficient β_i were reported by federal states where the unemployment rate is also high, for example, Saxony, Saxony-Anhalt and Mecklenburg-West Pomerania in the German case and the city states of Bremen and Hamburg in the West German case. According to theory, β_i should reflect the movements of the regional unemployment rate because of movements of the national unemployment rate. As seen before, the unemployment rates of the East German federal states only slightly react to cyclical movements of the German unemployment rate. Hence, the regression coefficient seems to capture mainly a level effect of the unemployment rate and not the relationship of movements in the national and the regional unemployment rate. The sign of relative regional unemployment rate differentials is a straightforward hint on whether the regional unemployment rate is below or above the national average. In the case of β-differences, such straightforward interpretations are not possible. For instance, a negative value could also be the result of the difference between an above average unemployment rate and a strongly weighted national unemployment rate. This makes the level of relative regional unemployment rate β-differences difficult to interpret.

3.4 Testing for cross-sectional dependence

Studies examining the hypothesis of stochastic convergence usually apply unit root tests on relative regional unemployment rates. The low power of univariate unit root tests is well known. Therefore, recent studies apply panel unit root tests to gain additional power. While there are many different panel unit root tests, the choice of an appropriate test procedure is not trivial.

The so called first generation panel unit root tests assume that the cross-sectional units are independent, whereas the so called second generation unit root tests have relaxed this assumption. A number of studies indicate that investigating (non) stationarity in a panel framework might lead to serious problems if the assumption of cross-sectional independence is violated and this is not taken into account (see, for example, O'Connell 1998, Banerjee/Marcellino/Osbat 2004, 2005, and Baltagi/Bresson/Pirotte 2007). O'Connell (1998) and Baltagi/Bresson/Pirotte (2007) show that the first generation panel unit root tests tend to reject the non-stationarity hypothesis too often if the independency assumption does not hold.

Cross-sectional dependence is introduced in this framework in terms of the disturbances. The first generation panel unit root tests assume that the error terms $\varepsilon_{i,t}$ of the panel ADF-regression (see equation (2.25)) are independently and identically distributed. This implies that the covariance matrix $\Omega = E(\varepsilon_t \varepsilon_t')$ with $\varepsilon_t = (\varepsilon_{1,t}, \ldots, \varepsilon_{N,t})$ is diagonal and the off-diagonal elements of this matrix are zero.

This assumption is required when deriving the limiting distribution to test the null hypothesis of a unit root against the alternative hypothesis of a stationary process. O'Connell (1998) shows using the panel unit root test provided by Levin/Lin/Chu (2002) that the derived limiting distribution is no longer correct and the power diminishes if the off-diagonal elements are non zero.

This discussion shows that before choosing an appropriate panel unit root test, it is necessary to test the assumption of cross-sectional independence. In this case, cross-sectional independence requires that the error terms in an ADF-regression in a panel framework are not correlated. Hence, for each federal state, an ADF-regression for relative regional unemployment rates is estimated. Following Carrion-I-Silvestre/German-Soto (2009), the tests provided by Pesaran (2004) and Ng (2006) are used to examine whether the residuals from the ADF-regression exhibit cross-sectional correlation. In order to isolate serial correlation from cross-sectional correlation, two lags are allowed.

3.4.1 Two tests for cross-sectional dependence

The Cross Dependence (CD) test designed by Pesaran (2004) is easy to compute and builds on the average of (estimated) pair-wise Pearson's correlation coefficients $\hat{p}_j$, $j = 1, \ldots, n$ with $n = N(N-1)/2$ possible correlation relationships of a panel of N time series. The null hypothesis of cross-sectional independence is tested against the alternative hypothesis of dependence. The test statistic is given by:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{j=1}^{n} p_j \sim N(0,1) \qquad (3.6)$$

The null hypothesis that all units are uncorrelated is very extreme. Furthermore, it provides no information about the shape of cross-sectional dependence within the sample. Ng (2006) introduced a method which relies on the computation of spacings that overcomes some of these disadvantages. The procedure provides a global test on cross-sectional dependence but also an algorithm which allows splitting the whole sample in groups of different strength of cross-sectional dependence. Hence, the null hypothesis of cross-sectional dependence can not only be tested for the whole sample, but also for each subgroup separately. Compared to the CD-test, this approach reveals more information about the extent and nature of cross-sectional correlation within the sample.

The spacing test provided by Ng (2006) does not directly test whether the sample correlations are zero. The test is based on the probability integral transformation of the ordered correlation coefficients denoted by $\bar{\varphi}_j$. Ng (2006) shows that the spacings of the ordered and transformed correlation coefficients $\bar{\varphi}_j - \bar{\varphi}_{j-1}$ follows a stochastic process with well-defined properties if the sample correlations are zero. The approach suggested by Ng (2006) tests these properties.

The test procedure is as follows. In a first step, the absolute values of the estimated Pearson's correlation coefficients $\tilde{p}_j$ with $\tilde{p}_j = |\hat{p}_j|$ for all possible pairs of individuals $j = 1, 2, \ldots, n$ with $n = N(N-1)/2$ are calculated. The absolute values of the Pearson's correlation coefficients are applied to ensure that negative and positive correlations are treated symmetrically. Then, they are sorted in ascending order. This leads to a sequence of ordered statistics given by $\{\tilde{p}_{[1:n]}, \tilde{p}_{[2:n]}, \ldots, \tilde{p}_{[n:n]}\}$.

Let Φ denote the conditional distribution function of the standard Normal distribution. The probability integral transformed correlation coefficients $\bar{\varphi}_j$ are defined as $\Phi(\sqrt{T}\tilde{p}_{[j:n]})$ so that $\bar{\varphi} = (\bar{\varphi}_1, \ldots, \bar{\varphi}_n)$. The spacings are defined as $\Delta\bar{\varphi}_j = \bar{\varphi}_j - \bar{\varphi}_{j-1}$. Ng (2006) proposes splitting the sample of ordered spacings and arbitrarily portioning the sample in a group of small (S) correlation coefficients and a group of large (L) correlation coefficients. Let υ denote the share of pairs of correlation relationships in group S with $\upsilon \in (0,1)$. Therefore, the number of correlation relationships in group S is given by υn. The definition of the partition is carried out through the minimization of the sum of squared residuals:

$$Q_n(\upsilon) = \sum_{j=1}^{|\upsilon n|}(\Delta\bar{\varphi}_j - \bar{\Delta}_S(\upsilon))^2 + \sum_{j=|\upsilon n|+1}^{n}(\Delta\bar{\varphi}_j - \bar{\Delta}_L(\upsilon))^2 \tag{3.7}$$

where $\bar{\Delta}_S(\upsilon)$ and $\bar{\Delta}_L(\upsilon)$ denote the mean spacings for each group. A consistent estimate of the break point is obtained as $\hat{\upsilon} = \arg\min_{\upsilon\in(0,1)} Q_n(\upsilon)$.

After partitioning the correlations into the two groups S and L, the next step consists in testing the hypothesis of no correlation for the subsamples. However, group S and group L represent censored samples. Testing for cross-sectional correlation in censored samples is problematic because the distribution of the correlations under the null hypothesis is no longer well-defined.

Defining $\bar{\varphi}_j^n = n\bar{\varphi}_j$ and the corresponding spacings as $\Delta\bar{\varphi}_j^n = \bar{\varphi}_j^n - \bar{\varphi}_{j-1}^n$. Furthermore, the q-order spacings are defined as $\Delta\bar{\varphi}_{jq}^n = \bar{\varphi}_j^n - \bar{\varphi}_{j-q}^n$. Ng (2006) shows that under the null hypothesis of no cross-sectional correlation, it holds that $\Delta\bar{\varphi}_j^n$ is asymptotically uncorrelated and the mean of q-order spacings are linear in q. To test for cross-sectional dependence in the subsamples, Ng (2006) suggest a spacings variance ratio test (SVR test) to examine both properties. Let η denote the size of the sample and let:

$$\hat{\mu}_1 = \frac{1}{\eta - 1}\sum_{k=1}^{\eta}(\bar{\varphi}_k^n - \bar{\varphi}_{k-1}^n) \tag{3.8}$$

$$\hat{\mu}_q = \frac{1}{\eta - q} \sum_{k=q+1}^{\eta} (\bar{\varphi}_k^n - \bar{\varphi}_{k-q}^n) \tag{3.9}$$

$$\hat{\sigma}_1^2 = \frac{1}{\eta} \sum_{k=1}^{\eta} (\bar{\varphi}_k^n - \bar{\varphi}_{k-1}^n - \hat{\mu}_1)^2 \tag{3.10}$$

$$\hat{\sigma}_q^2 = \frac{1}{q(\eta - q)} \sum_{k=q+1}^{\eta} (\bar{\varphi}_k^n - \bar{\varphi}_{k-q}^n - \hat{\mu}_q)^2 \tag{3.11}$$

Ng (2006) shows that under the null hypothesis that all correlation coefficients are jointly zero:

$$SVR\,(\eta) = \frac{\hat{\sigma}_1^2}{\hat{\sigma}_q^2} - 1 \sim N(0, \omega_q^2) \tag{3.12}$$

where $\omega_q^2 = (2(2q-1)(q-1))/3q$. In actual testing, the standardized spacings variance ratio test (*svr*-test) is used that is standard normally distributed under the null hypothesis:

$$svr(\eta) = \frac{\sqrt{\eta}\, SVR\,(\eta)}{\sqrt{\omega_q^2}} \sim N(0,1) \tag{3.13}$$

The correlation coefficients are sorted in ascending order. Hence, a rejection of the null hypothesis of no cross-sectional correlation for the small correlation sample *S* will always imply rejection of the null hypothesis for the large correlation sample *L*.

Ng (2006) points out that it is difficult to identify mean shifts occurring at the two ends of the sample. Hence, some trimming is required. Following Ng (2006), the smallest and largest 10 percent of $\bar{\varphi}_j$ are not used for determining the breakpoint. Furthermore, to compute the *q*-ordered spacings for the *svr*-test statistic, this chapter also follows Ng (2006) and *q* is set to 2.

3.4.2 Results

This section presents the results for the two cross-sectional correlation tests provided by Pesaran (2004) and Ng (2006). Both test were applied to investigate whether residuals of ADF-regressions for West German federal states and all German federal states respectively exhibit cross-sectional correlation. All three different measures for relative regional unemployment rates are considered.

Table 3.1: Results CD-test by Pesaran (2004)

	Germany	West Germany
regional unemployment β-differentials	-2.111*	-2.935*
regional unemployment differentials	-2.005*	-2.847*
regional unemployment ratios	-1.859	-2.844*
Source: Own calculations, * denote significant on the five percent level.		

The results of the CD test by Pesaran (2004) are reported in table 3.1. For West Germany, the null hypothesis of cross-sectional independence is rejected in all three cases at the five percent level. The degree of cross-sectional dependence appears to be very similar for all three measures. For Germany, the null hypothesis is rejected on the five percent level for regional unemployment differentials and β-differentials. For relative unemployment rates measured as ratios, the null hypothesis is still rejected on the ten percent level.

Table 3.2: Results Germany spacing-test by Ng (2006)

	Germany		
	$\hat{\upsilon}$	svr_S	svr_L
regional unemployment β-differentials	0.183	-1.552	2.107*
regional unemployment differentials	0.292	-0.670	2.925*
regional unemployment ratios	0.208	0.813	3.077*
Source: Own calculations, * denote significant on the five percent level.			

Table 3.2 reports the result of the spacing test by Ng (2006).[1] Column $\hat{\upsilon}$ contains the share of the possible correlation relationships in group *S*. Column svr_S contains the *svr* test statistic for group *S*, and column svr_L the *svr* test statistic for group *L*.

In the case of Germany, the null hypothesis of no cross-sectional dependence can not be rejected for group *S*, but is rejected for group *L* for all three measures of relative regional unemployment rates on the five percent level. Investigating the evolution of relative regional unemployment rates graphically already showed that federal states in East Germany and West Germany behave differently. This might be one of the reasons why for group *S* the hypothesis of cross-sectional independence is not rejected in all three cases. The value of $\hat{\upsilon}$ corresponds to the share of all the 120 possible correlation pairs between the 16 German federal states assigned to

1 The MATLAB code for the spacing test provided on Serena Ng's homepage is used here (http://www.columbia.edu/sn2294/research.html).

group *S*. The number of correlation pairs in group *S* differs between 22 and 35. Therefore, it can be concluded that cross-sectional dependence is present among the majority of the German regions.

Table 3.3: Results West Germany spacing-test by Ng (2006)

	West Germany		
	$\hat{\upsilon}$	svr_S	svr_L
regional unemployment β-differentials	0.578	2.280*	–
regional unemployment differentials	0.333	−1.146	2.179*
regional unemployment ratios	0.244	0.865	0.428

Source: Own calculations, * denote significant on the five percent level.

For the West German federal states, the results are rather mixed (see table 3.3). In the case of the β-differentials, the hypotheses of cross-sectional independence is rejected for group *S*. This result for group *S* implies a rejection of the null hypothesis also for group *L* (see Ng 2006). For the regional unemployment differentials, the null hypothesis is rejected for group *L*. But $\hat{\upsilon}$ takes on a value of 0.333, which means that only one third of the correlation pairs are assigned to group *S* and two thirds to group *L*. For the relative regional unemployment rates measured as ratios, the null hypothesis can neither be rejected for group *S* nor group *L*. Based on these findings, calculating relative regional unemployment ratios appears to be an appropriate way for West German federal states to annihilate common movements in regional unemployment rates. Furthermore, the development of regional unemployment rates and the West German unemployment rate appears to be characterized by similar relative changes during the last decades.

Reasons for cross-sectional dependence mentioned in the literature are for instance common trends or cyclical behavior. The tests for cross-sectional dependence were applied to relative regional unemployment rates. Usually, relative regional unemployment rates are constructed to account for common movements and to examine the region-specific evolution of regional unemployment. Nevertheless, the tests provide clear evidence that cross-sectional dependence is still present in relative regional unemployment rates. These results give a hint that the regional unemployment rates are actually characterized by common movements, but that these common movements affect regional unemployment rates differently. Otherwise, they would have been eliminated by the construction of relative regional unemployment rates.

The results show that in general, relative regional unemployment rates are characterized by cross-sectional dependence. To test the hypothesis of stochastic convergence, it is necessary to resort to second generation panel unit root tests to take the cross-sectional dependence into account.

3.5 Testing the hypothesis of stochastic convergence

Recent developments in panel unit root tests account for the presence of cross-sectional dependence through the specification of approximate factor models. These tests model cross-sectional dependence via common factors shared by all cross-sectional units and provide test statistics for the cross-sectionally adjusted time series. So called second generation panel unit root tests of this kind are provided by Bai/Ng (2004), Moon/Perron (2004), and Pesaran (2007b).

According to Banerjee/Wagner (2009), the PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common Components) approach by Bai/Ng (2004) is the least restrictive procedure while the other two methods can be considered as special cases of the PANIC approach. The framework by Bai/Ng (2004) allows both the common factors and the remaining idiosyncratic component to follow a $I(1)$ process, while the procedure of Moon/Perron (2004) requires the common factors to be $I(0)$ and the procedure by Pesaran (2007b) allows for one stationary common factor only. Hence, the results from the PANIC approach provide the necessary information whether the underlying assumptions about the common factors in the tests by Moon/Perron (2004) and Pesaran (2007b) are valid. Therefore, this chapter follows the approach proposed by Bai/Ng (2004).

The basic idea of the procedure proposed by Bai/Ng (2004) is to decompose the time series into common factors and idiosyncratic terms, and then test each of these components for a unit root. Bai/Ng (2004) show that it is possible to obtain consistent estimators of the common factors and the idiosyncratic terms by applying the method of principal components to first-differenced data. This is independent of the dynamic properties of underlying time series. Hence, the test for the number of common factors does not depend on whether the idiosyncratic components are stationary and vice versa. Banerjee/Wagner (2009) consider this as the most important feature of the analysis by Bai/Ng (2004).

3.5.1 Modeling cross-sectional dependence via approximate factors

The illustration of the method of principal components to estimate the common and idiosyncratic factors in this section follows Bai/Ng (2004). They assume that the data generating process (DGP) for a variable $x_{i,t}$, where i denotes the cross-sectional dimension with $i = 1 \ldots N$, and t denotes the time dimension with $t = 1 \ldots T$, can be described as:

$$x_{i,t} = D_{i,t} + u_{i,t} \tag{3.14}$$

where $D_{i,t}$ denotes the deterministic part of the process that can consist of a constant and/or a trend whereas $u_{i,t}$ is the stochastic part. Further, it is assumed that the stochastic component $u_{i,t}$ of the process is driven by two forces: common factors shared by all cross-sectional units and an idiosyncratic individual-specific component. Examples for such common factors are cyclical development or technological change. Hence, common factors capture the co-movement of the economic time series and the cross-sectional correlation. Let F_t denote a r x 1 vector of r common factors, ξ_i the corresponding factor loadings, and $e_{i,t}$ the idiosyncratic component. Thus the DGP can be written as:

$$x_{i,t} = D_{i,t} + \xi_i' F_t + e_{i,t} \tag{3.15}$$

$$(1-L)F_t = C(L)\eta_t \tag{3.16}$$

$$(1-\rho_i L)e_{i,t} = H_i(L)\varepsilon_{i,t} \tag{3.17}$$

where $C(L) = \sum_{j=0}^{\infty} C_j L^j$ and $H_i(L) = \sum_{j=0}^{\infty} H_{ij} L^j$. Assumptions (3.16) and (3.17) imply that the DGP of the idiosyncratic component $e_{i,t}$, and the DGP of the r common factors, can be described as a first order autoregressive process. The idiosyncratic component $e_{i,t}$ follows a $I(1)$ process if $\rho_i = 1$ and is stationary if $|\rho_i| < 1$. Furthermore, Bai/Ng (2004) allow each of the r common factors to follow a stationary or a non-stationary process. r_0 common factors are assumed to follow a $I(0)$ process and r_1 common factors to follow a $I(1)$ process, with $r = r_0 + r_1$. The aim of the PANIC approach by Bai/Ng (2004) is to determine r_1 and to test if $\rho_i = 1$.

The common factors and the idiosyncratic components are both unobserved and unknown. Hence, the main difficulty is to determine the number of factors r. Further, estimations of the two components have to be consistent when it is not known a priori whether they are $I(1)$ or $I(0)$. Bai/Ng (2004) suggest to use a principal component method to decompose the time series into its common components and an idiosyncratic component. If equation (3.15) contains only an intercept, first differences are taken to eliminate the shift term and then the principal component method is applied to the model in first differences. The DGP corresponding to equation (3.15) in first differences is given by:

$$\Delta x_{i,t} = \xi_i' \Delta F_t + \Delta e_{i,t} \tag{3.18}$$

with $t = 2, 3, \ldots, T$ and $i = 1, 2, \ldots, N$. Let $f_t = \Delta F_t$ and $z_{i,t} = \Delta e_{i,t}$. Hence, equation (3.18) can also expressed as:

$$\Delta x_{i,t} = \xi_i' f_t + z_{i,t} \tag{3.19}$$

Next, define:

$$X = (x_1, x_2, \ldots, x_N) \tag{3.20}$$

as the $T \times N$ matrix of all observations where:

$$x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,T})' \tag{3.21}$$

$\tilde{X}$ is the corresponding $(T-1) \times N$ matrix of the data in first differences:

$$\tilde{X} = \Delta X = (\Delta x_1, \Delta x_2, \ldots, \Delta x_N) \tag{3.22}$$

Following Bai/Ng (2004), the principal component estimator $\hat{f}$ of $f = (f_2, f_3, \ldots, f_T)$ is $(T-1)^{(1/2)}$ times the r eigenvectors corresponding to the r largest eigenvalues of the $(T-1) \times (T-1)$ matrix $\tilde{X}\tilde{X}'$.

The optimal number of common factors r can be determined by using the information criterions provided in Bai/Ng (2002). Following Banerjee/Wagner (2009) and Carrion-I-Silvestre/German-Soto (2009), the optimal number of common factors is determined by the information criterion BIC_3 provided in Bai/Ng (2002). According to the simulations by Bai/Ng (2002), this information criterion has very good properties in the presence of cross-sectional correlation. In this case, the BIC_3 computed for r^* common factors is given by:

$$BIC_3(r^*) = V(r^*, \hat{F}^{r^*}) + r^* \hat{\sigma}^2 \left(\frac{(N + T^* - r^*)\log(NT^*)}{NT^*} \right) \tag{3.23}$$

with $V(r^*, \hat{F}^{r^*}) = N^{-1} \sum_{i=1}^{N} \hat{\sigma}_i^2$, where $\hat{\sigma}_i^2 = \hat{z}_{i,t}' \hat{z}_{i,t} / T^*$ and $T^* = T - 1$. To determine the optimal number of common factors r, the maximal number of common factors permitted was set to five.

After determining the optimal number of common factors, it is possible to estimate the corresponding factor loadings given by $\hat{\xi}$. Under the normalization $\hat{f}'\hat{f} / (T-1) = I_r$, where I_r is the $r \times r$ identity matrix, the estimated factor loadings are obtained from the relationship $\hat{\xi} = \tilde{X}'\hat{f} / (T-1)$.

Next, the idiosyncratic components $\hat{z}_{i,s}$ can be computed as:

$$\hat{z}_{i,s} = \Delta x_{i,s} - \hat{\xi}_i' \hat{f}_s \tag{3.24}$$

Note, the common factors as well as the idiosyncratic components are still written in first differences. However, the main concern is to examine equation (3.15) and not equation (3.18). It is possible to recover the estimated factors by summation. Define for $t = 2, 3, \ldots, T$:

$$\hat{F}_t = \sum_{s=2}^{t} \hat{f}_s \tag{3.25}$$

and

$$\hat{e}_{i,t} = \sum_{s=2}^{t} \hat{z}_{i,s} \tag{3.26}$$

If equation (3.15) contains an intercept and a deterministic trend, it is necessary to take first differences to eliminate the shift term and to demean the data to eliminate the deterministic trend. After taking first differences and demeaning the data, the method of principle components described above can be applied to the panel.

Note, here bounded variables are considered. As discussed in section 2.1.2, the assumption of a deterministic trend appears to be inappropriate in the case of a bounded variable. Trend behavior of a bounded variable appears to be better characterized by a stochastic trend. Hence, it appears to be appropriate to assume that the deterministic part is characterized by a constant only and not by a constant and a linear trend. Therefore, the analysis here only considers the case of only an intercept.

3.5.2 Testing for a unit root

Non-stationarity of the time series $x_{i,t}$ can result from a unit root in the idiosyncratic component and/or from a unit root in the common component. For the case of a unit root in all series $x_{i,t}$, it is sufficient that at least one non-stationary common factor is present if this factor is loaded in all series. That is what Bai/Ng (2004) call integration or non-stationarity due to a pervasive source. If all common factors are stationary, a series $x_{i,t}$ has a unit root if and only if $e_{i,t}$ has a unit root. Bai/Ng (2004) call this non-stationarity due to a series-specific source. Therefore, appropriate unit root tests for the idiosyncratic and the common component are required.

The idiosyncratic component can be tested for a unit root by applying an ADF test on every single series. Even after controlling for cross-sectional dependence, the power of the univariate unit root test remains low. However, Bai/Ng (2004) suggest two tests for the pooled data that focus on the pooled *p*-values from univariate ADF tests for each time series of the panel. Let $p_{\hat{e}}(i)$ denote the *p*-value associated with the univariate ADF test for the idiosyncratic component $\hat{e}_{i,t}$ from the *i*th cross-sectional unit, $i = 1, \ldots, N$. The BN_N test which parallels the test proposed by Choi (2001) for cross-sectional independent panels is given by:

$$BN_N = \frac{-2\sum_{i=1}^{N}\log p_{\hat{e}}(i) - 2N}{\sqrt{4N}} \Rightarrow N(0,1) \tag{3.27}$$

The BN_{χ^2} test which parallels the procedure proposed by Maddala/Wu (1999) is given by:

$$BN_{\chi^2} = -2\sum_{i=1}^{N}\log\, p_{\hat{e}}(i) \sim \chi^2_{(2N)} \tag{3.28}$$

Choosing a test for a unit root in the common factor depends on the number of common factors. If there is only a single common factor, which means $r = 1$, a unit root can be tested for by using an univariate ADF test.[2] Bai/Ng (2004) show that the ADF test for the estimated common factor in the intercept only case denoted by $\mathrm{ADF}^c_{\hat{F}}$, has the same limiting distribution as the ADF test for the constant only case.[3]

In the case of more than one common factor, Bai/Ng (2004) provide two tests for the number of linearly independent $I(1)$ common trends contained in the common factors. This is equivalent to examining the co-integration rank of the common factors (see Banerjee/Wagner 2009). Both test statistics are computed recursively with the first test statistic based on $r = m$ common factors. This means that in the first step, the null hypothesis of r stochastic trends given by $m = r$ is tested against the alternative hypothesis of $m = r - 1$. The recursive test procedure ends when the first non-rejection of the null hypothesis occurs.

The $MQ^c_c(m)$ test corrects for serial correlation of arbitrary form by non-parametrically estimating the relevant nuisance parameters. Let $\hat{F}^c_t = \hat{F}_t - \bar{\hat{F}}_t$ with $\bar{\hat{F}}_t = (T-1)^{-1}\sum_{t=2}^{T}\hat{F}_t$. This procedure is based on estimating a VAR(1) process for $\hat{Y}_t$ with $\hat{Y}_t = \hat{\beta}\hat{F}^c_t$. $\hat{\beta}$ is the matrix of m eigenvectors associated with the m eigenvalues of the matrix given by $1/T^2\sum_{t=2}^{T}\hat{F}^c_t\hat{F}^{c\prime}_t$. Let $\hat{\varepsilon}_t$ denote the residuals from the VAR(1) process and let:

$$\Sigma^* = \sum_{j=1}^{J}K(j)\left(T^{-1}\sum_{t=2}^{T}\hat{\varepsilon}_{t-j}\hat{\varepsilon}_t\right) \tag{3.29}$$

---

2 Note, F_t is a matrix of size $r \times T$. This means that the matrix of common factors is not characterized by the structure of the underlying panel. The size of this matrix only depends on the number of observations in time but not on the number of cross-sectional units. Hence, if there is only one common factor, an univariate unit root test is sufficient.

3 In the case of an intercept and a trend, the ADF test for the estimated common factor has the same limiting distribution as the ADF test for the case with a constant and a linear trend.

where $K(j) = 1 - j/(J+1)$ with $j = 0, 1, \ldots, J$. Let $\hat{v}_c^c(m)$ be the smallest eigenvalue of:

$$\hat{\Phi}_c(m) = 0.5\left[\sum_{t=2}^{T}(\hat{Y}_t\hat{Y}_{t-1}' + \hat{Y}_{t-1}\hat{Y}_t') - T(\Sigma^* + \Sigma^{*\prime})\right]\left(\sum_{t=2}^{T}\hat{Y}_{t-1}\hat{Y}_{t-1}'\right)^{-1} \tag{3.30}$$

The test statistic of the $MQ_c^c(m)$ test is given by:

$$MQ_c^c(m) = T[\hat{v}_c^c(m) - 1] \tag{3.31}$$

In contrast, the $MQ_f^c(m)$ test filters the factors under the assumption that they have a finite order VAR representation. The test statistic is constructed in a similar way as before. In this case, first a pth order VAR is estimated for $\Delta\hat{Y}_t$ to obtain $\hat{\Pi}(L) = I_m - \hat{\Pi}_1 L - \ldots - \hat{\Pi}_p L^p$. Then, $\hat{\Pi}(L)$ is used to filter $\hat{Y}_t$ to get $\hat{y}_t = \hat{\Pi}(L)\hat{Y}_t$. Let $\hat{v}_f^c(m)$ be the smallest eigenvalue of:

$$\hat{\Phi}_f(m) = 0.5\left[\sum_{t=2}^{T}(\hat{y}_t\hat{y}_{t-1}' + \hat{y}_{t-1}\hat{y}_t')\right]\left(\sum_{t=2}^{T}\hat{y}_{t-1}\hat{y}_{t-1}'\right)^{-1} \tag{3.32}$$

The test statistic of the $MQ_f^c(m)$ test is given by:

$$MQ_f^c(m) = T[\hat{v}_f^c(m) - 1] \tag{3.33}$$

Critical values for both tests can be found in Bai/Ng (2004).[4]

3.5.3 Results

Table 3.4 reports the estimated optimal number of common factors for each series based on the BIC_3 provided by Bai/Ng (2002).[5] In all cases, the optimal number of common factors was well below the maximum number of factors that was permitted. With regard to German and West German relative regional unemployment differentials and β-differentials, one common factor is found. For the regional unemployment ratios, two common factors are found in the case of Germany. For the case of West Germany, no common factor is found. This result is in line with the findings of the spacing test by Ng (2006). Only for West German relative regional unemployment ratios, the no-correlation hypothesis was not rejected for both group S and group L.

4 In the case of an intercept and a linear trend, testing the number of linear independent stochastic trends is similar to the procedure described above. However, the so called $MQ_c^\tau(m)$ test and $MQ_f^\tau(m)$ test are based on the residuals from a regression of $\hat{F}_t$ on a constant and a time trend denoted by $\hat{F}_t^\tau$ instead of $\hat{F}_t^c$ (see Bai/Ng 2004).

5 The MATLAB code for the PANIC approach provided on Serena Ng's homepage is used for the empirical analysis in this section (http://www.columbia.edu/ sn2294/research.html).

Table 3.4: Estimated optimal number of common factors

	Germany	West Germany
regional unemployment β-differentials	1	1
regional unemployment differentials	1	1
regional unemployment ratios	2	0

The panel unit root tests by Choi (2001) and Maddala/Wu (1999) applied in this section, as well as the pooled BN_N test and the BN_{χ^2} test for the idiosyncratic component, are based on the *p*-values of univariate ADF tests. For these univariate ADF tests, a heterogeneous lag length was allowed to control for serial correlation. The optimal number of lags was determined by the sequential *t*-test suggested by Ng/Perron (1995).

Table 3.5: Results first generation panel unit root tests

	Choi (2001)	Maddala/Wu (1999)
Germany		
regional unemployment β-differentials	10.085*	112.676*
regional unemployment differentials	16.301*	162.408*
regional unemployment ratios	7.183*	89.463*
West Germany		
regional unemployment β-differentials	2.485*	35.716*
regional unemployment differentials	0.705	24.458
regional unemployment ratios	5.180*	52.762*
Source: Own calculations, * indicate rejection of the unit root null hypothesis at the five percent critical level.		

Table 3.5 presents the results for the panel unit root test provided by Choi (2001) and Maddala/Wu (1999) for relative regional unemployment rates. Of course, these first generation panel unit root tests are only appropriate for relative regional unemployment rate ratios in the case of West Germany where no cross-sectional correlation was detected. In all other cases, the tests might lead to biased results because the independency assumption is violated. However, these findings of the first generation panel unit root tests serve as a reference to get an impression of how sensitive these first generation panel unit root tests react to the presence of cross-sectional dependence in the case of (West) German regional unemployment rates.

In the case of Germany, the first generation panel unit root tests indicate for the existence of stochastic convergence. Both tests reject the hypotheses of a unit root in relative regional unemployment rates in all three cases at the five percent level. For West Germany, the results are mixed. Both tests find a unit root in relative regional unemployment rate differentials but not for the relative regional unemployment rate β-differentials. In addition, for regional unemployment rate ratios, the hypotheses of a unit root is strongly rejected. Because in this case the assumption of cross-sectional independence is valid, the results can be interpreted as evidence of stochastic convergence for West German regional unemployment rate ratios.

Table 3.6 presents the results for the decomposed time series. The first two columns report the findings of the BN_N test and the BN_{χ^2} test for the idiosyncratic component of the relative regional unemployment rates. The last three columns present the results for the common component. If there is one common factor, an ADF test can be applied to test for a unit root. The results of the $ADF^c_{\hat{F}}$ test are presented in the third column. However, two common factors were identified for German relative regional unemployment rate ratios. Here, the $MQ^c_c(m)$ test and the $MQ^c_f(m)$ test are applied to determine the number of linear independent stochastic trends.

Table 3.6: Results PANIC approach by Bai/Ng (2004)

	BN_N	BN_{χ^2}	$ADF^c_{\hat{F}}$	$MQ^c_c(m)$	$MQ^c_f(m)$
Germany					
regional unemployment β-differentials	6.431*	83.450*	-5.588*	–	–
regional unemployment differentials	3.590*	60.718*	-3.391*	–	–
regional unemployment ratios	-1.117	23.068	–	2	2
West Germany					
regional unemployment β-differentials	5.080*	52.129*	-2.491	–	–
regional unemployment differentials	2.319*	34.667*	-2.117	–	–

Source: Own calculations, * indicate rejection of the unit root null hypothesis at the five percent critical level.

For Germany, the null hypothesis of a unit root in the idiosyncratic component is rejected for regional unemployment differentials and β-differentials. For the regional unemployment ratios, the null-hypothesis of a unit root can not be rejected.

For the common components of German relative regional unemployment rates, the results are also mixed. For regional unemployment rate differentials and β-differentials, the hypothesis of a unit root in the common factor is rejected at the five percent level. In the case of regional unemployment rate ratios, the results of the $MQ^c_c(m)$ test and the $MQ^c_f(m)$ test indicate that both common factors are non-stationary and not co-integrated.

For West Germany, the hypothesis of a unit root in the idiosyncratic component is rejected for relative regional differentials and for relative regional β-differentials. However, the hypothesis of a unit root can not be rejected for the common factor of these two measures.

According to the definition of stochastic convergence given in section 3.3, relative regional unemployment rates have to follow a stationary process. If relative regional unemployment rates exhibit no cross-sectional dependence, a first generation panel unit root test is sufficient to test the hypothesis of stochastic convergence. Hence, the results for West German regional unemployment rate ratios can be interpreted as evidence of stochastic convergence. In the case of cross-sectional dependence, a second generation panel unit root test has to be applied. In this case, stochastic convergence requires both the idiosyncratic component as well as the common component to follow a stationary process. Hence, only the findings for German relative regional unemployment rate differentials and β-differentials can be interpreted as evidence for the existence of stochastic convergence. In contrast, the hypothesis of stochastic convergence has to be rejected for German relative regional unemployment rate ratios and West German relative regional unemployment rate differentials as well as β-differentials.

These results show two important facts. When examining the evolution of regional unemployment disparities and testing the hypothesis of stochastic convergence, the existence of cross-sectional correlation should be taken into account. Otherwise, the hypothesis of non-stationarity appears to be usually over rejected. The first generation panel unit root tests in general tend to favor the hypothesis of stochastic convergence whereas the results from the PANIC approach are much more mixed. Especially the results for West Germany are in contrast to the findings in the existing literature. Moreover, the construction of relative regional unemployment rates appears to be of great importance. The three measures of relative regional unemployment rates correspond to three different assumptions about the shape of the equilibrium relationship between the regional unemployment rate and the national unemployment rate. The analysis shows that the results are very sensitive with respect to these assumptions. Hence, the choice of a certain measure is a crucial decision that affects whether evidence of stochastic convergence is found or not.

The cyclical sensitivity model provides useful information about the appropriate equilibrium relationship. Nevertheless, it appears to give rough hints rather than exact references. For West Germany, the results of the cyclical sensitivity model are not unambiguous. Regional unemployment β-differentials and regional unemployment ratios could both be appropriate measures. The results of the spacing test by Ng (2006) show that relative regional ratios capture cross-sectional dependence better than regional β-differentials. The panel unit root test rejects the hypothesis of a unit root for West German regional unemployment ratios but not for β-differences. For German federal states, the results of the cyclical sensitive model favored regional unemployment ratios to describe the equilibrium relationship. However, relative regional unemployment rate differences and β-differences are found to be stationary.

These results indicate that region-specific shocks might have long-lasting effects on relative regional unemployment rates. There are two different ways to think about region-specific shocks (see, for example, Choy/Maré/Mawson 2002). A region-specific shock can be described as a shock that exclusively affects a particular region. Furthermore, a nationwide shock that has disproportional impact on particular regions, can also be considered as region-specific. Because of the construction of relative regional variables, common shocks or common movements that affect all regions in the same way are removed. Hence, the identified common factors in relative regional unemployment rates can be considered as movements common to all regions but with a different impact on regional unemployment rates. Or, to state it differently, these are common factors loaded with a different weight in each time series of the panel. In the case of West Germany, the PANIC approach rejects the hypothesis of stochastic convergence because the common factors contain a unit root, whereas the idiosyncratic component of relative regional unemployment rates follows a stationary process. Hence, non-stationarity of West German relative regional unemployment rates is primarily observable due to a pervasive source. This means shocks that exclusively affect a certain region appear to have rather temporary effects and do not trigger a rise in regional unemployment disparities. According to the findings presented in this section, common shocks that affect regions in a different way appear to be the main source of regional unemployment disparities.

3.6 Conclusion

This chapter examined the evolution of regional unemployment disparities for West German federal states and all German federal states including East Germany. The rank-order stability test indicates that the geographic distribution of regional unemployment rates in Germany was very stable during the last twenty years. Only in the 1980s West Germany was characterized by a high degree of intra-distributional dynamics.

Evidence of β-convergence was found for West German federal states but not for all German federal states. This means there is a negative relationship between regional unemployment rates and their corresponding growth rates in West Germany, but not for all German federal states. The existence of β-convergence gives a hint that there might be some form of catching-up process between favorable and unfavorable regions. However, a negative relationship between regional unemployment rates and their corresponding growth rates is only a necessary but no sufficient condition that the gap between favorable and unfavorable regions becomes smaller and regional inequality decreases. This means the existence of β-convergence does not imply σ-convergence.

Using the coefficient of variation as an inequality measure shows that the inequality in 2009 is actually lower compared to the initial year 1968. Furthermore, the coefficient of variation for all German states in 2009 is higher compared to the initial year 1991. Nevertheless, these results should not be interpreted as evidence for a convergence process in West Germany and for divergence between East and West German federal states. The evolution of the coefficient of variation shows that periods of increasing inequality alternate with periods of decreasing inequality. Therefore, measuring σ-convergence and hence β-convergence strongly depends on the two points in time considered. Especially during the last twenty years regional inequality seems to be mainly driven by cyclical movements and not by a continuous transition process.

While a favorable economic climate leads to a rise of regional inequality, regional inequality decreases during economic crisis. This means that during a boom, the unemployment rate decreases slower in regions with high unemployment rates compared to those with low unemployment rates. During an economic downturn, however, unemployment increases slower in regions with high unemployment rates compared to those with low unemployment rates. Therefore, a positive economic climate is not sufficient to close the gap between low unemployment regions and high unemployment regions.

The results from these different cross-sectional approaches are a sign that regional unemployment rates in Germany may not be characterized by a transition process. Changes in the dispersion of regional unemployment appear to be mainly driven by region-specific shocks due to economic disturbances. Therefore, the hypothesis of stochastic convergence appears to be more appropriate to investigate the evolution of regional unemployment disparities in Germany. The presence of stochastic convergence requires a stable long-run relationship between the regional unemployment rates and their national counterpart. According to the literature, three different assumptions can be made about the shape of this equilibrium relationship. To get an impression about the sensitivity of the results with regard to these assumptions all three approaches are considered here. The hypothesis of stochastic convergence is examined for relative regional unemployment rate differentials, relative regional unemployment rate ratios and relative regional unemployment rate β-differentials. In the case of stochastic convergence, these relative regional unemployment rates have to follow a stationary process.

First, the panel unit root tests provided by Choi (2001) and Maddala/Wu (1999) are applied. These so called first generation panel unit root tests usually favor the hypothesis of stochastic convergence. These results are in line with the findings from previous studies using first generation panel unit root tests.

However, such first generation panel unit root tests are only appropriate if cross-sections are not correlated. Otherwise, they tend to reject the hypothesis of non-stationarity too often. The results of the cross-sectional dependence tests suggested by Pesaran (2007b) and Ng (2006) indicate that in most cases the independence assumption is violated for relative regional unemployment rates of (West) German federal states. So called second generation panel unit root tests relaxing the independence assumption appear to be more appropriate than first generation panel unit root tests.

Here the PANIC approach provided by Bai/Ng (2004) is used to tests the hypothesis of stochastic convergence. The basic idea of the PANIC approach is to decompose the underlying time series into common factors which capture cross-sectional correlation and an idiosyncratic region-specific term, and then testing each of these components for a unit root.

This chapter finds evidence of stochastic convergence in the case of German regional unemployment differentials and β-differentials as well as for West German regional unemployment ratios. In all other cases the convergence hypothesis is rejected. In the case of stochastic convergence, the idiosyncratic component as well as common components have to follow a stationary process. In general, the rejection of the hypothesis of stochastic convergence results from a so called pervasive source. This means that at least one common factor was found to contain a unit root. Hence, divergence of regional unemployment in Germany mainly occurs because of movements in regional unemployment rates that are common to all federal states but affect each federal state in a different way. In contrast, unemployment shocks that exclusively appear in a particular federal state, seem to have only transitory effects.

The results of the PANIC approach are rather mixed. This is in contrast to the results of the panel unit tests by Choi (2001) and Maddala/Wu (1999) but also to the findings of previous studies using first generation panel unit root tests. However, these results emphasize the necessity to account for cross-sectional dependence when analyzing stochastic convergence of regional unemployment rates. Furthermore, the findings appear to be sensitive in terms of the underlying assumption about the long-run relationship between regional unemployment rates and their national counterpart. Hence, the choice for a particular measure for relative regional variables is not trivial. These aspects should be taken into account in further research.

Chapter 4

4 Convergence analysis for heterogeneous employment groups

The literature review in chapter 2.1 shows that the large body of literature about convergence of regional labor markets focuses on the evolution of regional unemployment disparities. In contrast, little is known about the evolution of regional employment disparities. However, the results of OECD (2000) and OECD (2005) show that regional unemployment disparities and regional employment disparities might behave differently. To get a comprehensive overview about the evolution of regional labor market disparities, it appears to be necessary to examine both unemployment as well as employment. Therefore, this chapter deals with the question whether regional employment disparities within West Germany narrow, widen or remain constant over time.

The number of unemployed exhibits a clear positive trend during the last two decades whereas the number of employees remained remarkably stable during this time. Nevertheless, German employment is characterized by a clear change in the skill composition. As in most of the developed countries, the number of low-skilled workers decreased and the number of high-skilled workers increased. This decline of job opportunities for low-skilled workers and the rise of job opportunities for high-skilled workers is usually considered a result of the so called skill-biased technological change. This means technological progress favors high-skilled employment, whereas jobs for low-skilled workers get lost (see, for example, Acemoglu 1998, 2002 or Spitz-Oener 2006). Other explanations are an increase in international competition promoting specialization in human-capital intensive industries (see Wood 1994, 2002) and organizational changes (see Lindbeck/Snower 1996).

The findings of several studies suggest that regions are affected differently by the change of the skill composition. For example, regions with a large share of high-skilled workers show higher employment growth rates compared to low-skilled regions (see, for example, Glaeser/Scheinkman/Shleifer 1995, Simon 1998, Simon/Nardinelli 2002, Blien/Südekum/Wolf 2006, Shapiro 2006, Südekum 2008, and Schlitte 2011). However, it is far from clear whether this triggers convergent or divergent behavior of regional labor market disparities. The aim of this chapter is to examine in which way the change in the skill composition of employment affects the evolution of regional employment disparities. Hence, this chapter provides convergence analysis for total employment as well as for different subgroups of skill-specific employment.

Note, that studies investigating the role of (un)employment subgroups in association with the evolution of regional disparities is only very scarce. To the best of my knowledge, Südekum (2008) is the only study examining regional convergence for an employment subgroup. Südekum (2008) examines the hypothesis of β-convergence for the share of high-skilled employment for West German districts and the time period 1977 to 2002. His results indicate that convergence has occurred within regions and within single industries, but that the speed of convergence differs. Hence, Südekum (2008) concludes that regional disparities in regional skill composition decrease over time.

Grip/Hoevenberg/Willems (1997) examine the hypothesis of convergence for atypical employment in the European Union where atypical employment contains part-time employment and temporary employment. They provide a convergence index that examines the dispersion of shares of atypical employment within different occupation groups across Europe. The value of the indicator at any point in time is a measure of the degree of harmonization between the countries. This means Grip/Hoevenberg/Willems (1997) follow the concept of σ-convergence. Note, they do not chose a regional approach, but compare different countries. Nevertheless, it appears to be appropriate to mention this study here, because the findings show that employment subgroups, more precisely, different occupation groups within atypical employment, might behave differently. For part-time employment, none of the occupational groups shows clear convergence tendencies. However, for production and agricultural workers, significant divergence behavior is observable. However, in the case of temporary employment, several occupation groups show a slight converging trend, particularly professional and agricultural workers, while clerical workers show divergent tendencies. These results indicate that employees are not a homogeneous group and divergent and convergent behavior might be found for employment subgroups.

It is far from clear how the different behavior of employment subgroups affects the evolution of total employment.[1] Divergence of total employment might simply reflect the divergent behavior of one employment subgroup only, while all other employment subgroups show convergent behavior. Furthermore, it is possible that total employment shows convergent behavior even if several employment subgroups exhibit divergence. In this case, the geographical distribution of employment might be stable. However, there would be a remarkable change in the geographical distribution of the employment prospects of the different subgroups. This means that if analyzing total employment indicates that employment prospects are evenly distributed across regions, this does not imply that the employment prospects for different employment subgroups are also evenly distributed across regions.

1 Unfortunately, also Grip/Hoevenberg/Willems (1997) present no results for total part-time employment and total temporal employment respectively.

Hence, if employment subgroups behave differently, the analysis of regional total employment can only provide limited insights into the evolution of regional employment disparities. Considering different employment subgroups appears to be a fruitful extension of the existing literature.

As seen in the literature review, studies about convergence of regional unemployment disparities usually focus on the unemployment rate, whereas various measures are used to operationalize employment, for example, employment growth, the employment rate, or shares of employment subgroups. This chapter focuses on the employment rate.

The employment rate is preferred compared to the absolute employment level as well as employment growth for several reasons. Using the number of employees in a region has the disadvantage that regions differ in size. Due to the size effect, there will always be a gap between the number of employees in large and small regions and hence persistent labor market disparities. Examining changes in the number of employees provides only limited information of the evolution of regional employment disparities. Convergence of regional employment growth rates allows no straightforward conclusion about the evolution of regional disparities in employment opportunities. Assume that all regions are equal in size but the number of employees differs across regions. Then different employment growth rates are necessary to close the gap between the regions whereas identical employment growth rates would trigger divergence. This is what the concept of β-convergence says.

Furthermore, the change in the skill composition of employment is usually considered as reflecting increasing job opportunities for high-skilled workers and decreasing job opportunities for low-skilled workers. The employment rate is defined as the share of the population that is employed. Hence, it reflects the employment prospects of the inhabitants of a certain region. In contrast, a high employment growth rate only says that the employment opportunities increase faster than in other regions. Hence, the region with the highest employment growth rate is not necessarily the region with the highest employment prospects. Using a relative employment measure such as the employment rate is in line with studies about regional unemployment disparities that examine the unemployment rate rather than regional unemployment levels or unemployment growth rates. Employment rates were calculated for total employment as well as for high-skilled, medium-skilled and low-skilled employment.

Skill-specific employment rates are considered here instead of employment shares for the three qualification groups because the main interest of this study is to investigate the evolution of regional employment disparities. Examining employment shares of different skill groups provides information on the evolution of the skill composition of employment across regions. However, the evolution of the skill composition of regional employment allows no straightforward conclusion about the evolution of regional employment opportunities. A rise as well as a decline of the differences in regional employment might go in hand in hand with a stable skill composition of regional employment over time.

For the sake of comparability to the existing literature and the availability of data, the previous chapter focused on German federal states. However, focusing on administrative areas like federal states or districts (NUTS3) causes the problem that borders of such areas are typically the results of political decisions or historical reasons. In general, they do not reflect the distribution of economic activity in space or cannot be regarded as economically independent because functional labor markets extend across administrative borders. An analysis of the dynamics of regional labor market disparities neglecting spatial dependencies runs the risk of capturing only a part of the ongoing processes. For example, an increasing employment rate in a rural area may not be the result of a positive economic development, but of employees moving from a city district to the rural area although still working in the city.

In this study, functional labor markets in West Germany are the unit of analysis. More specifically, the regional planning units (Raumordnungsregionen) provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (Bundesinstitut für Bau-, Stadt- und Raumforschung - BBSR) serve to delineate functional labor markets. Based on commuting flows, the German districts were aggregated to 96 units. Here the 71 West German regional planning units are used. The BBSR divides West Germany into 74 regional planning units, where the city state of Hamburg and the city state of Bremen represent own regional planning units. According to the BBSR, the regional planning units "Schleswig-Holstein Sued", "Hamburg-Umland-Sued" and "Hamburg" are aggregated to the analysis region "Hamburg" as well as "Bremen-Umland" and "Bremen" to the analysis region "Bremen". Considering these city states isolated from their hinterland is not appropriate with regard to functional labor markets.

The analysis is restricted to West Germany because the education system of West and East Germany before reunification was very different. Hence, the formal qualification level on what this study is forced to focus on, is not comparable in the 1990s. Furthermore, data on level of regional planning units for East Germany is only available since the mid 1990s. This means only short time series are available when including East Germany.

As in the previous chapter, this chapter also follows various concepts of convergence to get a comprehensive picture about the evolution of regional employment disparities. The traditional approach to investigate the hypothesis of stochastic convergence would be to compute deviations of regional employment rates from the West German average and test these deviations for a unit root. The previous chapter showed that there are several approaches to computing such relative regional variables. These approaches differ in the underlying assumption about the shape of the equilibrium relationship between the regional variables and their national counterpart. However, the previous section also showed that the results might be sensitive with respect to these assumptions. The definition of stochastic convergence imposes several restrictions that have to hold in the case of stochastic convergence. This section will show that it is possible to examine whether these restrictions are valid by applying the PANIC approach by Bai/Ng (2004) on the original time series. This appears to be a more convenient approach to test the hypothesis of stochastic convergence compared to the traditional way. No assumptions about the equilibrium relationship between the regional variables and their national counterpart are required. Further, it is no longer necessary to test the hypothesis of cross-sectional correlation.

The reminder of the chapter is as follows. The first section describes the underlying data for the analysis. Section 4.2 provides some stylized facts about the evolution of regional employment in West Germany. Convergence analysis following the cross-sectional approach is presented in section 4.3. The restrictions imposed by the definition of stochastic convergence and how these restrictions can be tested applying the PANIC approach by Bai/Ng (2004) is presented in section 4.4. Section 4.5 presents the results for the tests for stochastic convergence. The final section concludes.

4.1 Data and definitions

The employment rate corresponds to the relation between employment and the working age population. The employment rate is calculated as the ratio of employees between 15 and 64 years, measured by place of residence, and the working age population. The working age population are all people between 15 and 64 years. Data on employment is provided by the German Federal Employment Agency. It includes all employees subject to social security contributions. Data on the population is provided by the BBSR. The time series covers the period 1989 to 2008.[2]

In addition to total employment, this chapter also considers employment groups with different qualification levels. These three groups consist of employees without any vocational qualification (low-skilled workers), employees with completed apprenticeship (medium-skilled workers), and employees with completed tertiary

2 Data on employment measured by place of residence is only available as of 1989.

education (high-skilled workers). Skill-specific employment rates are calculated to analyze the evolution of regional disparities for these employment subgroups. The skill-specific employment rates correspond to the ratio of employees between 15 and 64 years in one of the qualification groups and the working age population. Hence, the employment rates for the three qualification groups sum up to the total employment rate.

Note, this chapter does not apply the original qualification measure provided by the Statistic Service of the Federal Employment Agency, but instead a corrected qualification measure. The reason is the fast growing and by now very large share of employees with unknown qualification level. In 1989, this share was 5.4 percent but increased to up to 16.0 percent in 2008.[3] On the regional level, there is much more variation. The share of employees with an unknown qualification level in 2008 differs between 8.3 percent in Ostwuerttemberg, and 24.3 percent in Schleswig-Holstein Nord. This can be regarded as a reference that the validity of the qualification measure decreased over time and this should be taken into account when using this measure.

There are three common ways to handle this problem. The first way is to exclude employees with unknown qualifications from the analysis. However, this would mean that for some regions, up to one quarter of the employees are no longer considered. The second way is to assume that all employees with unknown qualification levels have no vocational qualification and to assign them to the group of low-skilled workers. Another possibility is to assume that the employment share of the three qualification groups for employment with unknown qualification levels corresponds to the employment share of the three qualification groups for employment with a known qualification level. If this assumption holds, the employees with unknown qualification levels can be assigned to the three qualification groups according to these employment shares for total employment (with known qualification level).[4]

Here a different way is used to account for the rising share of workers with unknown qualification. The underlying assumptions to assign the employees with unknown qualification to the three qualification groups are very restrictive. In fact, the share of employees with unknown qualification levels differs considerably not only between the regions but also between occupations and sectors. In addition, for occupations and sectors there appears to be a certain degree of correlation between a large employment share of low-skilled workers and a large employment share

3 Therefore, with an average annual growth rate of 6.1 percent, the group of employees with an unknown qualification was the fastest growing "qualification" group during the last two decades. The high-skilled employees follow with an average annual growth rate of 3.3 percent between 1989 and 2008.

4 Fitzenberger/Osikominuy/Völterz (2006) provide several deductive imputation procedures to take the shortcoming of the education variable into account. However, the imputation procedures are developed for a panel of individuals, whereas this study is based on aggregate data.

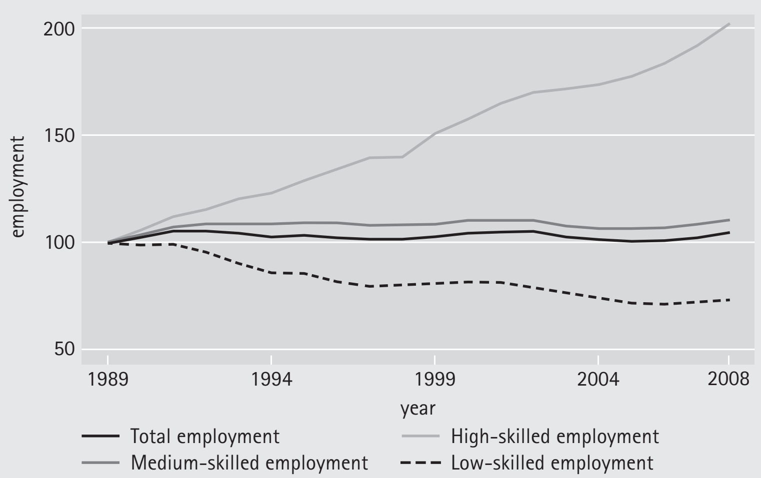
of employees with unknown qualification level. Nevertheless, a straightforward relationship between these two measures is not observable.

Here the starting point of the correction strategy are occupation groups on the three digit level. For each regional planning unit, it is assumed that the regional employment shares of the three qualification groups for employment with unknown qualification level in a certain occupation group corresponds to the regional employment shares of the three qualifications for employment with known qualification level in this occupation group. According to these shares, the employees with an unknown qualification level are assigned to the three qualification groups. This leads to the number of low-skilled, medium-skilled and high skilled workers for each occupation group in the considered regional planning unit. To get skill-specific regional employment, the number of employees in the three qualification groups are aggregated across the occupation groups. Aggregating the number of skill-specific employees for all regional planning units leads to West German skill-specific employment.

4.2 The evolution of skill-specific employment in West Germany

Figure 4.1 shows the development of employment in West Germany. The number of employees during the last 20 years was surprisingly stable. The number of employees in 2008 is about five percent higher than in 1989 (21,705,000 compared to 20,724,300). However, this difference seems to be the result of cyclical movements in employment.

Figure 4.1: Development of West German employment, index: 1989 = 100

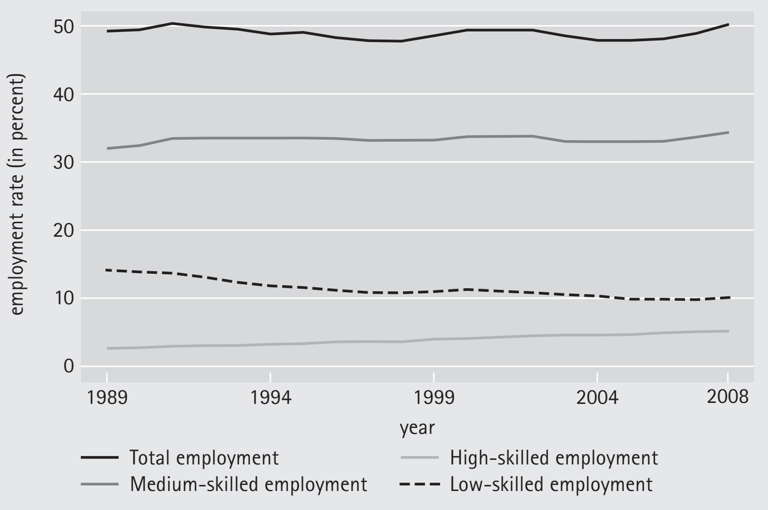


Source: Statistic of the German Federal Employment Agency, own calculations.

Although, neither a positive nor a negative trend is observable for West German employment, this does not hold for the regional planning units. 15 regions have lost employment during the last 20 years whereas 29 regions exhibit a clear positive trend in employment (see figure A.1 in the appendix). Hence, the stable number of employees in West Germany is not the result of stable regional employment. Jobs get lost in one region and new jobs are created in another region.

Figure 4.1 reveals that the qualification structure of the employees changed remarkably over time. On the one hand, high-skilled workers doubled in number from 1,186,600 in 1989 up to 2,399,200 in 2008. On the other hand, the number of low-skilled workers diminished by 27.1 percent from 6,054,200 to 4,414,400. The majority of employees belongs to the group of medium-skilled workers. The number of workers in this group also increased between 1989 and 2008. But the employment growth rate for this group with 10.4 percent was considerably smaller compared to that of the high-skilled workers.

Figure 4.2: Development of West German employment rates, 1989–2008



Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

In addition, the evolution of the employment rates reflects the changes in the skill composition of employment (see figure 4.2). The total employment rate remained remarkably stable during the whole observation period with 49.2 percent in 1989 and 50.3 percent in 2008. It fluctuated around a mean of 49.0 percent with its highest value in 1991 (50.6 percent) and its lowest value in 2005 (47.8 percent). The high-skilled employment rate doubled between 1989 to 2008 from 2.8 percent up to 5.6 percent. The low-skilled employment rate decreased by almost one third from 14.4 percent in 1989 to 10.2 percent in 2008. The low-skilled employment rate is still considerably higher than the high-skilled employment rate. Furthermore, a slight increase in the medium-skilled employment rate from 32.0 percent in 1989 to 34.5 percent in 2008 is observable.

The levels of the employment rates considerably differ between regions. In 2008, the regional total employment rates range between 56.9 percent in Schwarzwald-Baar-Heuberg and 44.4 percent in Trier and Ost-Friesland, a difference of 12.5 percentage points (see figure A.2 in the appendix). The distance between the highest and lowest medium-skilled employment rate is similar with 10.7 percentage points. Westmittelfranken reported the highest medium-skilled employment rate with 40.4 percent, whereas the lowest medium-skilled employment rate with 29.1 percent could be found in Bonn (see figure A.4 in the appendix). However, the high and low-skilled employment rates exhibit the largest regional differences. The highest value for the low-skilled employment rate in 2008 was reported in Schwarzwald-Baar-Heuberg (15.7 percent). It is two times higher than in Lueneburg (7.8 percent) (see figure A.5 in the appendix). Only 2.5 percent of the working age population in Ost-Friesland are high-skilled employees. In Munich, the high-skilled employment rate amounts to 11.3 percent and is more than four times higher than in Ost-Friesland (see figure A.3 in the appendix). Further, the geographical distribution of total employment rates and low-skilled employment rates is characterized by a large degree of similarity. In contrast, the geographical distribution of total employment rates and high-skilled employment rates clearly differs. This means that only regions that provide job opportunities for low-skilled workers can realize above average total employment rates. Or, to state it differently, regions with high employment prospects are those regions where low-skilled people also might get a job.

For every region, an increase of the high-skilled employment rate and a decrease of the low-skilled employment rate is observable (see figure A.3 and figure A.5 in the appendix). Hence, regional high-skilled and low-skilled employment rates across West Germany followed a common trend. Although, the West German total employment rate was higher in 2008 compared to 1989, eleven regional planning units reported a lower value in 2008 than in 1989. They were Schleswig-Holstein Ost, Duesseldorf, Rhein-Main, Starkenburg, Hochrhein-Bodensee, Neckar-Alb, Nordschwarzwald, Stuttgart, Bayerischer Untermain, Industrieregion Mittelfranken and Oberfranken-Ost. Note, that in 15 of the regional planning units, the number of employees decreased during the last 20 years whereas only eleven regional planning units reported a lower total employment rate in 2008 compared to 1989. This means that in some regions, a fall in the number of employees went hand in hand with a fall in the number of the working age population.

In Rhein-Main, Stuttgart and Munich, the medium-skilled employment rate decreased, whereas West Germany reported an increase of the medium-skilled employment rate. Nevertheless, for Stuttgart and Munich, the value of the total employment rate in 2008 exceeded the value in 1989. Hence, in these two regional planning units, the fall of the medium-skilled and the low-skilled employment rate was compensated by a rise in the high-skilled employment rate. In contrast, Rhein-Main belongs to the group of regional planning units with a decreasing total employment rate. The employment gains by the high-skilled were not sufficient to compensate the losses in medium- and low-skilled employment.

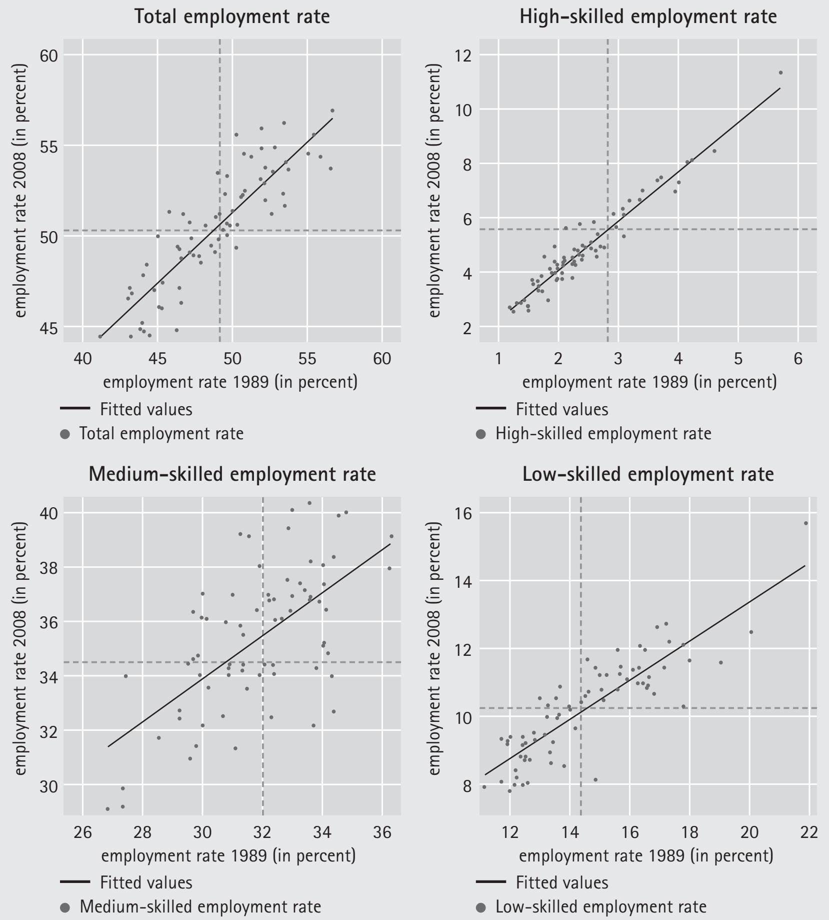
4.3 Recent trends in regional employment disparities

Similar to section 3.2, this section provides results for the cross-sectional approach to convergence. It examines the hypotheses of β-convergence and σ-convergence for regional total employment rates as well as for regional skill-specific employment rates. Furthermore, it investigates the intra-distributional dynamics of these measures.

To get a first impression of the persistence of regional employment disparities, the employment rates of each regional planning unit in 1989 and 2008 are plotted against each other (see figure 4.3). The dashed lines denote the corresponding West German rates in 1989 and 2008. These lines divide the panels of figure 4.3 into four areas. In the upper right area are regions with an above average employment rate in 1989 and an above average employment rate in 2008. In the bottom left area are regions with a below average employment rate in 1989 and a below average employment rate in 2008. The other two areas gather the regions that changed between these groups over time. In the upper left area are regions with a below average employment rate in 1989 and an above average employment rate in 2008. In the bottom right area are regions with an above average employment rate in 1989 and a below average employment rate in 2008.

Panel 1 of figure 4.3 shows that the ranking of the regional planning units according to their total employment rate has remained remarkably stable over time. The regression line has a slope of 0.78 and a R^2 of 0.76. With 0.87, the correlation coefficient for total employment rates in 1989 and 2008 is high. Regional planning units with high total employment rates in 1989 also report high total employment rates in 2008 and vice versa. Only ten of the 71 regional planning units changed their position relative to the West German total employment rate. Seven regions changed from the group of regions with an above average total employment rate to the group with a below average total employment rate. Three regions with a below average total employment rate in 1989 reported an above average total employment rate in 2008.

Figure 4.3: Persistence of regional employment rates



Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

For the high-skilled employment rates and the low-skilled employment rates, the results are very similar to the findings for the total employment rate. For the low-skilled employment rate, the regression line has a slope of 0.58 and a R^2 of 0.74 and the correlation coefficient is high with 0.86. There are only six regions which changed their groups (five from below average to the above average group and one from above average to the below average group). For the high-skilled employment rate, the relationship during the last twenty years is even more persistent. The regression line has a slope of 1.81 and a R^2 of 0.93. The correlation coefficient with 0.96 exceeds the value for the total employment rate as well as for the low-skilled employment rate. There are only four regions that changed their position with regard to the West German average.

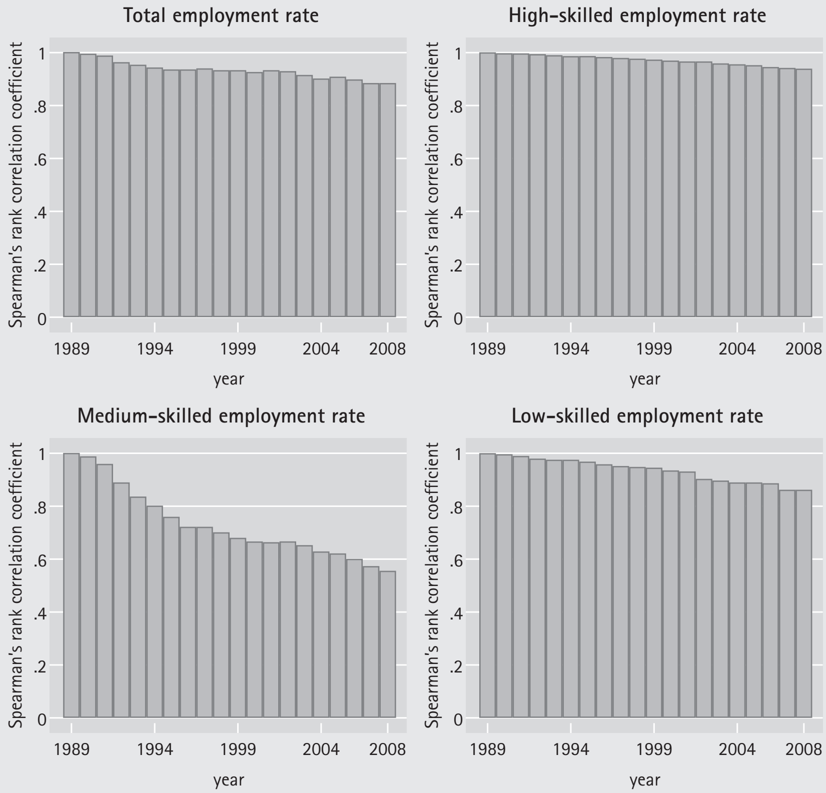
In contrast, the ranking of regional planning units according to the medium-skilled employment rate appears to be much weaker. There are 22 regional planning units that changed their position compared to the West German medium-skilled employment rate. 14 regions changed from the group with a below average medium-skilled employment rate to the above average group. Eight regions reported an above average medium-skilled employment rate in 1989 but a below average medium-skilled employment rate in 2008. The medium-skilled employment rate exhibits with 0.62 the lowest correlation coefficient of all employment rates under consideration. The regression line has a slope of 0.79 and a comparatively small R^2 of 0.38.

These results indicate that the total employment rate, the high-skilled employment rate and the low-skilled employment rate are characterized by a low degree of intra-distributional dynamics. In contrast, the geographical distribution of the medium-skilled employment rate exhibits more dynamics. Following Baddeley/Martin/Tyler (1998) and Martin (1997), the intra-distributional dynamics are examined in more detail by investigating the rank-order stability of regional employment rates over time. To test the rank-order stability, a Spearman's rank correlation coefficient is calculated for every year with 1989 as the reference year.

Figure 4.4 shows a slight decrease of the rank correlation coefficient for the total employment rate, the high-skilled employment rate and the low-skilled employment rate. In all three cases, the ranking of the regions according to the employment rate is very stable over time. The rank correlation coefficient in 2008 still exceeds 0.85 in all three cases. In contrast, clear changes in the rank order are observable for the medium-skilled employment rate. In 2008, the rank correlation coefficient is only 0.55. Especially in the 1990s, a sharp decrease of the rank correlation coefficient is observable. Between 1999 and 2003, the rank correlation coefficient remained stable followed by a slight decrease until 2008. The results confirm that the ranking of regions according to the medium-skilled employment rate are less persistent between 1989 and 2008, and that there is considerably more fluctuation here compared to other employment rates.

Hence, the medium-skilled employment rate was characterized by a strong degree of intra-distributional dynamics during the 1990s, whereas no similar pattern was found for the other employment rates. These findings are somewhat surprising. The medium-skilled workers are by far the largest group of employees. Thus, it seems reasonable to expect that the medium-skilled employment rate and the total employment rate show similar characteristics. However, this is not the case. It should kept in mind that the development of total employment is not first and foremost driven by the largest employment subgroup, but instead by the most dynamic employment subgroup (in absolute terms). The changes in high-skilled employment and low-skilled employment were more pronounced than the changes in medium-skilled employment. Therefore, changes in total employment also appear to be mainly driven by these two measures and they overlay the development of medium-skilled employment. This implies that the ranking of total employment rates is also more similar to the ranking of high- and low-skilled employment rates compared to the ranking of medium-skilled employment rates.

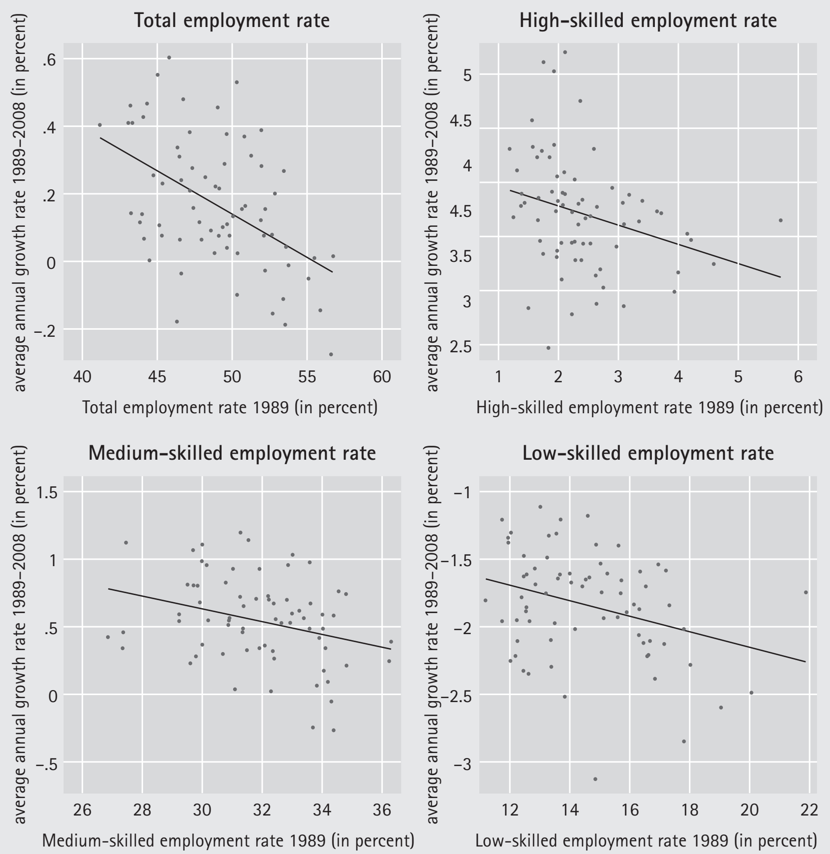
Figure 4.4: Rank-order stability of regional employment rates



Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

Further information about the evolution of regional employment disparities provides the concept of β-convergence and the concept of σ-convergence. Figure 4.5 presents the relationship between the initial value of the employment rate in 1989, and their average annual growth rate between 1989 and 2008. A negative relationship between these two measures can be interpreted as evidence of (unconditional) β-convergence.

Figure 4.5: Relationship between regional employment rates in 1989 and their average annual growth rates 1989–2008



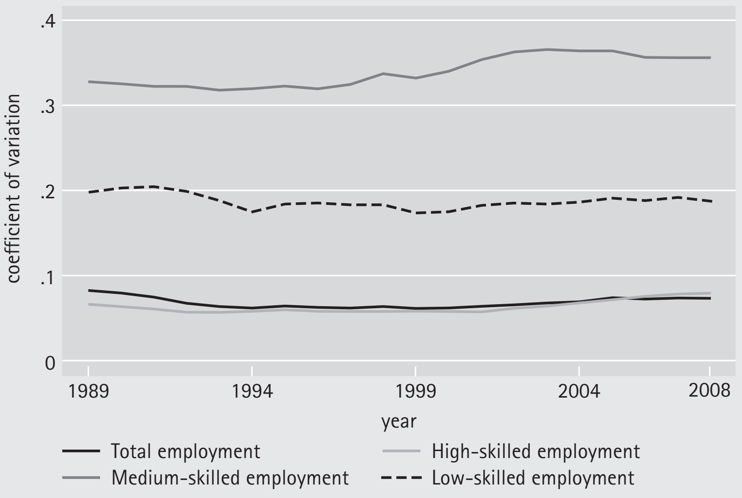
Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

Indeed, for employment rates shown in figure 4.5, a negative relationship is observable. The regression coefficients are significantly different from zero on the five percent level. But the coefficients are only small (total employment rate: -0.03, high-skilled employment rate: -0.18, medium-skilled employment rate: -0.05, low-skilled employment rate: -0.06). Further, the value of the adjusted R^2 shows that the initial level of the employment rate explains only a small part of the variation in the growth rate of total and skill-specific employment rates (total employment rate: 0.23, high-skilled employment rate: 0.07, medium-skilled employment rate: 0.08, low-skilled employment rate: 0.08). These results can be interpreted as evidence of the existence of weak (unconditional) β-convergence.

To examine whether the existence of β-convergence leads to a decrease in regional inequality, the evolution of the dispersion of regional employment rates is considered in figure 4.6. As in section 3.2, the coefficient of variation is applied as an inequality measure.

Figure 4.6 reveals that regional high-skilled employment rates are characterized by the highest degree of dispersion followed by the low-skilled employment rate. The coefficient of variation is smaller for the medium-skilled employment rate and the total employment rate. For these two measures, the coefficient of variation is nearly identical. For the high-skilled employment rate, a clear increase in the regional dispersion is observable between 1999 and 2003. From then on, the coefficient of variation remains stable. In contrast, medium-skilled, low-skilled and total employment rates, neither exhibit a clear positive nor clear negative trend over time with regard to the regional dispersion.

Figure 4.6: Dispersion of regional employment rates



Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

Figure 4.6 shows that for regional employment rates, the existence of β-convergence does not go hand in hand with the existence of σ-convergence. Regional inequality across West German regional planning units according to their employment rates appears to be persistent and provides no sign of a catching-up process. The evolution of the coefficient of variation neither indicates a clear convergent behavior nor a clear divergent behavior of regional employment rates during the last 20 years.

Section 3.2 showed that changes in the dispersion of regional unemployment rates are mainly driven by the business cycle. However, such a relationship is only hard to observe for regional employment rates. The cyclical movement of the dispersion of regional total employment rates and regional medium-skilled employment appears to be very weak. For low-skilled employment, the cyclical behavior of the dispersion is slightly more pronounced. An explanation might be that the number of employees clearly exceeds the number of unemployed. Therefore, during an economic downturn, the outflows from employment compared to the number of employees is less pronounced than the inflows into unemployment compared to the number of unemployed. Hence, the dispersion of regional unemployment reacts more sensitively to changes in the economic climate than does the dispersion of regional employment. This would also explain why cyclical movements appear to be slightly more pronounced for low-skilled workers. The risk of job loss is larger for this employment group than for the other employment groups. Further, for this group it is most clearly observable that an economic downturn leads to more equality, whereas a boom increases regional inequality.

Regional medium-skilled employment rates are characterized by intra-distributional dynamics during the 1990s. However, these changes in the ranking of the regions due to their medium-skilled employment rate did not affect the dispersion of employment rates across the regions. Regional total employment rates, high- and low-skilled employment rates are characterized by both a persistent distribution across regions, as well as persistent regional inequality. This is in line with the findings for regional unemployment rates.

The results show that regional employment rates are not characterized by transition dynamics. The results for the concept of β-convergence indicate that the value of the employment rate in the initial period can only explain a small part of the variation of the corresponding average annual growth rate for the time period 1989 to 2009. Therefore, also for regional employment rates, the concept of stochastic convergence appears to be more appropriate.

4.4 Stochastic convergence and cross-sectional dependence

The traditional approach to investigate the hypothesis of stochastic convergence, consists of calculating relative regional variables and testing them for a unit root. Banerjee/Wagner (2009) discuss in detail the restrictions imposed by the definition of stochastic convergence that have to hold for relative regional variables to follow a stationary process. Following the discussion in Banerjee/Wagner (2009), this section will show that an alternative approach to test the hypothesis of stochastic convergence would be to examine directly whether these restrictions are valid or not. Further, this section shows that applying the PANIC approach by Bai/Ng (2004) on the original time series instead of relative regional variables, provides all necessary information about the restrictions imposed by the definition of convergence.

4.4.1 Structures and restrictions imposed by the definition of stochastic convergence

Let $X_t = (x_{1,t}, \ldots, x_{N,t})'$ denote the joint vector of a regional variable $x_{i,t}$. If X_t is $I(0)$, this would imply that all regions are in their equilibrium and, therefore, shocks only have transitory effects. In this case, the hypothesis of stochastic convergence would be valid because if X_t is $I(0)$, the differences between the regions also have to be $I(0)$. Here, X_t is assumed to follow a $I(1)$ process. According to Banerjee/Wagner (2009), under appropriate assumptions, the Granger-type representation of this vector is given by:

$$\begin{pmatrix} x_{1,t} \\ \vdots \\ x_{N,t} \end{pmatrix} = \begin{pmatrix} C_1 \\ \vdots \\ C_N \end{pmatrix} \eta_t + \begin{pmatrix} D_1 \\ \vdots \\ D_N \end{pmatrix} T_t + c^*(L)\varepsilon_t \tag{4.1}$$

where η_t denotes the vector $r \geq 1$ of linearly independent common stochastic trends, T_t the vector of s deterministic components of the data generating process, and $c^*(L)\varepsilon_t$ the stationary part. Following Evans/Karras (1996), the definition of stochastic convergence for this variable is given by:

$$\lim_{t \Rightarrow \infty} E(x_{i,t} - a_t) = \mu_i \tag{4.2}$$

where a_t denotes a joint common trend. The definition of stochastic convergence maintains that the deviations of the regional variable $x_{i,t}$ from the common trend a_t follow a $I(0)$ process. However, it is not possible to test equation (4.2) because the common trend a_t is unobservable and unknown. In general, the cross-sectional average $\bar{x}_t$ where $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{i,t}$ is used as a proxy for the common trend (see also section 2.1.2). This leads to the following definition of stochastic convergence:

$$\lim_{t \Rightarrow \infty} E(x_{i,t} - \bar{x}_t) = \mu_i \tag{4.3}$$

Let $C_i = (c_{i,1}, \ldots, c_{i,r})$ and $D_i = (d_{i,1}, \ldots, d_{i,s})$. Further, let $\bar{c}^*(L) = N^{-1}\sum_{i=1}^{N} c^*(L)\varepsilon_t$. According to Banerjee/Wagner (2009), the corresponding cross-sectional average $\bar{x}_t$ can be expressed in the following fashion:

$$\bar{x}_t = \frac{1}{N}\sum_{i=1}^{N} c_{i,1}\eta_{1,t} + \ldots + \frac{1}{N}\sum_{i=1}^{N} c_{i,r}\eta_{r,t} + \frac{1}{N}\sum_{i=1}^{N} d_{i,1}T_{1,t} + \ldots + \frac{1}{N}\sum_{i=1}^{N} d_{i,s}T_{s,t} + \bar{c}^*(L)\varepsilon_t \tag{4.4}$$

Hence, if the hypothesis of stochastic convergence holds, calculating the deviations of each time series of the panel from the cross-sectional average has to eliminate all stochastic trends as well as all non-constant deterministic terms. Only in this case, the stationary terms remain after computing relative regional variables. Banerjee/Wagner (2009) show that this means that the stochastic terms in equation (4.1) and equation (4.4) are given by:

$$c_{i,k} - \frac{1}{N}\sum_{i=1}^{N} c_{i,k} = 0 \tag{4.5}$$

for all $i = 1, \ldots, N$. Equation (4.5) implies that $c_{i,k} = c_k$ for all $i = 1, \ldots, N$ and for all $k = 1, \ldots, r$. Therefore, the definition of stochastic convergence allows for one common stochastic $I(1)$ trend given by $\eta_t = \sum_{k=1}^{r} c_k \eta_{k,t}$. Additionally, this stochastic trend has to be loaded with the same weight in each series. Furthermore, the coefficient of each non-constant deterministic part has to be identical for each time series of the panel. This in turn implies that the definition of stochastic convergence does not allow for different linear trend slopes in the data.[5]

In this $I(1)$ setting, the hypothesis of stochastic convergence requires that the idiosyncratic component of the regional variable follows a stationary process. Further, non-stationarity of $x_{i,t}$ is only allowed to occur via one common factor with homogeneous factor loadings that is $I(1)$. Otherwise, the hypothesis of stochastic convergence does not hold.

Because these two conditions have to be valid in the case of stochastic convergence, it is possible to distinguish between two sources of divergence. Divergence might occur because the idiosyncratic component of the regional variable follows a non-stationary process. This might be caused by developments that exclusively affect a particular region. Further, divergence might occur because the common components of the regional variable follow a non-stationary process and are loaded with heterogeneous weights in each time series of the panel. This could be the case if there are common developments that affect each region differently. Note, these origins of regional divergence are very similar to the definition of region-specific shocks given in Choy/Maré/Mawson (2002) (see also section 3.5.3). This emphasizes that region-specific shocks with long-lasting effects can be considered as the main source of regional divergence in the time series approach to convergence.

In this framework, the regional variables $x_{i,t}$ exhibit cross-sectional correlation because they contain common components. Relative regional variables are only free from cross-sectional correlation if there is only one common component characterized by homogeneous loadings. Only in this case is the common component eliminated by computing the deviations from the cross-sectional mean.

5 Note, this implies that trend-stationarity of relative regional variables is not a sufficient condition for the existence of stochastic convergence.

If the relative regional variables contain no common components, non-stationarity of the idiosyncratic component remains the only possible source of divergence. From this point of view, the assumption of cross-sectional independence is not only important for the choice of an appropriate panel unit root test, but also has a meaning in regard to contents. The assumption of cross-sectional independence for relative regional variables implies that total shocks affect each region in the same way. For example, there is a downturn in a particular industry and the regions are characterized by different degrees of specialization in terms of this industry. Such a form of a region-specific shock as a possible source of divergence would be excluded under the assumption of cross-sectional independence. However, the results from the previous chapter indicate that this assumption is only hard to verify. Shocks common to all regions but affecting regions in a different way seemed to be an important source of divergence of regional unemployment rates in Germany.

4.4.2 Testing stochastic convergence as a second generation panel unit root test

The definition of stochastic convergence given in Evans/Karras (1996) can be rewritten for regional employment rates $er_{i,t}$ as:

$$\lim_{t \Rightarrow \infty} E(er_{i,t} - a_t) = \mu_i \tag{4.6}$$

where i denotes the cross-sectional dimension with $i = 1, \ldots, N$, and t denotes the time dimension with $t = 1, \ldots, T$. a_t denotes a_t joint trend that is present in all N series of the panel. In the case of stochastic convergence, the deviations of the regional employment rates $er_{i,t}$ from the common trend a_t have to follow a stationary process.

If the regional employment rate is $I(0)$, this implies that also the differences between the regions are $I(0)$. Hence, in this case, the hypothesis of stochastic convergence holds. According to the discussion in section 4.4.1, if $er_{i,t}$ is $I(1)$, there are two conditions that have to be valid in the case of stochastic convergence. Firstly, even in the case of stochastic convergence, the regional employment rates are allowed to contain one common trend that follows a non-stationary process, this means a_t is $I(1)$. However, this common trend has to be shared by all regions in the same way. The common factor has to be loaded with the same weight in each time series of the panel. Secondly, the remaining idiosyncratic component of the regional employment rates has to be $I(0)$.

Note, these conditions can be tested by applying the PANIC approach by Bai/Ng (2004) introduced in section 3.5 on the original time series of a regional variable.

The PANIC approach combines the principal component method and unit root tests. In the first step, a principal component method is applied to decompose the different time series of the panel into their idiosyncratic components and the common components. This provides information about the (optimal) number of common factors present in the data and whether the corresponding factor loadings are heterogeneous or homogeneous. The second step of the PANIC approach consists of testing the idiosyncratic component and the common factors for a unit root. Therefore, the results from the PANIC approach applied on the original time series of a regional variables provides information about whether the variable is $I(0)$ or $I(1)$. Moreover, in the $I(1)$ case, it is possible to examine whether this variable is characterized by one non-stationary common trend with homogeneous factor loadings and a stationary idiosyncratic component.

In the context of stochastic convergence, the PANIC approach by Bai/Ng (2004) is not only a tool to test for a unit root in a panel if the cross-sectional units exhibit correlation. Further, the PANIC approach provides an appropriate framework to test the hypothesis of stochastic convergence by applying the combination of factor decomposition and unit root test to regional variables. In contrast to the traditional approach of testing the hypothesis of stochastic convergence, this approach makes it possible to directly test the restrictions imposed by the definition of stochastic convergence.

Applying the PANIC approach on the original time series to test the hypothesis of convergence, provides some additional advantages compared to the traditional approach to examine the hypothesis of stochastic convergence. As already mentioned before, the common trend process a_t is unobservable and unknown. To overcome this problem, the cross-sectional average of the variable of interest in general serves as a proxy for a_t.

As discussed in section 3.3, the literature provides several ways to calculate relative regional variables. They differ in the underlying assumption about the shape of the equilibrium relationship between the regional variables and their national counterpart. The results of the previous chapter indicate that the results for the hypothesis of stochastic convergence might be sensitive in terms of these assumptions. Using the PANIC approach, it is no longer necessary to account for a joint trend by calculating the deviations from the cross-sectional average. Instead, the time series is decomposed into its idiosyncratic and common components using the principal component method. Hence, in this case, no proxy for the common trend is required as well as no additional assumptions about the shape of the equilibrium relationship between the regional variables and their national counterpart.

The West German employment rate $\overline{er}_t$, can only serve as a proxy for one non-stationary joint trend with homogeneous factor loadings. If the time series of the panel are characterized by one or more joint trends with heterogeneous factor loadings, the deviations of $er_{i,t}$ from $\bar{er}_t$ still contain fragments of this common trend.

Hence, the calculation of relative regional variables corresponds to a factor decomposition of the original regional variable for one common factor loaded with the same weight in each series (see, for example, Banerjee/Wagner 2009). Therefore, applying the PANIC approach on relative regional variables means that the underlying time series of the panel are de-factored twice. The first time by the construction of relative regional variables. The second time by the principal component method. However, focusing on absolute regional variables instead of relative regional variables, means that the approximate factor model provides the original common factors. Otherwise, the common factors identified by the approximate factor model solely represent fragments of the common factor present in the original time series. In this case, information about the structure of the common factor could get lost. Hence, it seems to be appropriate to avoid a two time de-factorizing of the time series. Further, it is not a priori known whether relative regional variables exhibit cross-sectional correlation or not. This makes it necessary to test for cross-sectional dependence. The idea of the PANIC approach is to distinguish between common factors that trigger cross-sectional dependence in the data, and the remaining idiosyncratic component. Hence, tests for cross-sectional dependence become dispensable.

The hypothesis of stochastic convergence has to be rejected if the idiosyncratic component is $I(1)$, or if there are common factors with heterogeneous factor loadings that are $I(1)$. In the latter case, relative regional variables exhibit cross-sectional dependence because the construction of relative regional variables is no longer sufficient to eliminate the common trend. In addition, if the panel is characterized by cross-sectional correlation, non-stationarity of the deviations of $er_{i,t}$ from $\bar{er}_t$ would still imply that region-specific shocks have permanent effects on regional employment rates. However, divergence of regional employment rates might occur because the idiosyncratic component of the regional employment rates is stationary, but the fragments of a common trend are non-stationary and vice versa. In the first case, divergence would be the result of a shock common to all regions but affecting each region in a different way. In the second case, divergence occurs because shocks that exclusively affect a particular region have long-lasting effects.[6] In both cases the regional employment rates show divergent behavior. However, it appears to be fruitful to distinguish between the different origins of the divergence processes. For example, the results of the previous chapter for regional

6 Of course, divergence of regional employment rates might also occur because the idiosyncratic component is $I(1)$, and there is at least one common factor with heterogeneous factor loadings that is $I(1)$.

unemployment rates show that the hypothesis of stochastic convergence is usually rejected because of a non-stationary common factor with heterogeneous factor loadings. In contrast to the PANIC approach, simple univariate unit root tests are not able to distinguish between these two origins of divergence. The same is true for first generation panel unit root tests due to the assumption of cross-sectional independence.

To test the hypothesis of stochastic convergence for regional employment rates in West Germany, the restrictions imposed by the definition of stochastic convergence are directly considered. Instead of focusing on relative regional employment rates, the PANIC approach is applied to the original series. This allows to test for whether the assumptions imposed by the definition of stochastic convergence about the shape of the idiosyncratic component and common factors are valid or violated in the underlying data. Further, if the hypothesis of stochastic convergence is rejected, it can be examined what the sources of divergence in regional employment rates are.

4.5 Convergence or divergence of regional employment rates?

This section presents the results of the PANIC approach by Bai/Ng (2004) for regional total employment rates as well as for the regional skill-specific employment rates. Note, the employment rate is also a bounded variable just like the unemployment rate. Hence, it is again assumed that regional employment rates contain a constant but not a deterministic trend.

To choose the optimal number of common factors, the panel BIC_3 provided by Bai/Ng (2002) is used (see also section 3.5.1). Table 4.1 presents the optimal number of common factors identified by the principal component approach.

Table 4.1: Estimated optimal number of common factors in West German regional employment rates

	Common Factors
total employment rate	1
high-skilled employment rate	1
medium-skilled employment rate	2
high-skilled employment rate	1

Source: Own calculations.

For the medium-skilled employment rate, two common factors are identified. For the other employment rates, one common factor is identified. In the case of the total employment rate, the common factor captures the cyclical behavior of the total employment rate. For the high- and low-skilled employment rate, the common factor reflects the positive and the negative trend behavior of the time series respectively. The two common factors for the medium-skilled employment rate are harder to interpret. The first common factor seems to capture the cyclical behavior, while the second common factor seems to reflect the slight positive trend in medium-skilled employment.

Table 4.2: Results PANIC approach by Bai/Ng (2004)

	BN_N	BN_{χ^2}	$\text{ADF}^c_{\hat{F}_t}$	$MQ^c_c(m)$	$MQ^c_f(m)$
total employment rate	4.455*	217.07*	-3.482*	–	–
high-skilled employment rate	9.787*	306.93*	1.093	–	–
medium-skilled employment rate	-3.078*	90.13	–	2	2
low-skilled employment rate	-0.048	141.20	-1.902	–	–
Source: Own calculations, * denotes significance on the five percent level.					

Table 4.2 presents the results of the PANIC approach by Bai/Ng (2004) for total employment rates and the skill-specific employment rates. In the case of stochastic convergence, the idiosyncratic component has to follow a stationary process. The first two columns of table 4.2 present the results of the two pooled unit root tests for the idiosyncratic components BN_N and BN_{χ^2} suggested by Bai/Ng (2004) (for details see section 3.5.2).

For the idiosyncratic component of regional total employment rates as well as regional high-skilled employment rates, both tests reject the hypothesis of a unit root on the five percent level. This means that region-specific shocks occurring in a particular region have only transitory effects on the high-skilled employment rate. None of the regions deviates permanently from the single global trend identified for high-skilled employment and total employment. In contrast, the hypothesis of a unit root can not be rejected for the idiosyncratic component of the low-skilled employment rate. This means labor market shocks that exclusively affect a certain region, have persistent effects on low-skilled employment and influence their long-run behavior. Therefore, the hypothesis of stochastic convergence has to be rejected for regional low-skilled employment rates. For regional medium-skilled employment rates, the results for the idiosyncratic component are ambiguous. While the BN_N test rejects the hypothesis of a unit root on the five percent level, the unit root hypothesis can not be rejected by the BN_{χ^2} test.

Apart from the idiosyncratic component, the definition of stochastic convergence imposes several restrictions about the shape of the common factors. The common factor also has to follow a stationary process. However, the definition of stochastic convergence also allows for the presence of one non-stationary common factor with homogeneous factor loadings. In the case of the total employment rate, the high- and low-skilled employment rate, an ADF test is sufficient to test for a unit because only one common factor was identified. The result of this $ADF^c_{\hat{F}_t}$ test are presented in the third column of table 4.2. For the medium-skilled employment rate, more than one common factor was identified. Hence, the $MQ^c_c(m)$ test and the $MQ^c_f(m)$ test provided by Bai/Ng (2004) to examine the number of linearly independent $I(1)$ common trends contained in the common factors has to be applied (see also section 3.5.2). The result for these tests are presented in the last two columns of table 4.2.

For the medium-skilled employment rate, the results of the $MQ^c_c(m)$ test and the $MQ^c_f(m)$ test indicate that both identified common factors are $I(1)$. However, the definition of stochastic convergence allows for only one non-stationary common factor to be present in the data. Therefore, the hypothesis of stochastic convergence has to be rejected for the medium-skilled employment rate.

For the common factor of regional total employment rates, the $ADF^c_{\hat{F}_t}$ test rejects the hypothesis of the unit root on the five percent level. Because the common component reflects the cyclical movements of regional total employment rates, it is not surprising that the common factor is found to be stationary. In the case of the regional total employment rates, the results of the unit root tests for the idiosyncratic component and the common factor provide evidence of stochastic convergence.

In contrast, the $ADF^c_{\hat{F}_t}$ test favors the hypothesis of a unit root in the common factor of the low- and high-skilled employment rate. If the idiosyncratic component follows a stationary process as in the case of the high-skilled employment rate, the definition of stochastic convergence is in line with the existence of one non-stationary common factor. However, it requires that a stochastic common factor is loaded with the same weight in each time series. Therefore, it is necessary to consider the corresponding factor loadings in more detail.

Table 4.3: Description of factor loadings

	Mean	Std. Dev.	Min	Max	t-stat, H_0: $\xi_i = 1$
total employment rate ($\hat{F}^1$)	0.99	0.12	0.67	1.25	-0.51
high-skilled employment rate ($\hat{F}^1$)	0.95	0.32	0.46	2.24	-1.35
medium-skilled employment rate ($\hat{F}^1$)	0.98	0.21	0.45	1.44	-0.89
medium-skilled employment rate ($\hat{F}^2$)	0.07	1.00	-1.61	1.86	-7.79*
low-skilled employment rate ($\hat{F}^1$)	0.98	0.21	0.67	1.63	-0.90
Source: Own calculations, * denotes significance on the five percent level.					

Table 4.3 provides descriptive statistics about the factor loadings for regional employment rates. In most cases, the mean of the factor loadings is near unity. One exception are the factor loadings of the second common factor for the medium-skilled employment rate. Here, the mean of the common factor is near zero. Comparing the minima and the maxima as well as the standard deviation of the factor loadings, reveals that the factor loadings of the second factor of the medium-skilled employment rate exhibit a strong degree of variation across regions. This means that the slight positive trend in medium-skilled employment seems to affect the regions very differently.

A *t*-test is applied to examine the hypothesis that the factor loadings correspond to unity. The results are provided in the last column of table 4.3. Only for the second common factor of the medium-skilled employment rate does the *t*-test reject the null hypothesis of all factor loadings equalling unity. In all other cases, the null hypothesis is not rejected. Hence, the stochastic common factor present in the time series of the high-skilled employment rate appears to be loaded with the same weight in each series. Because the idiosyncratic component was found to be stationary, the restrictions imposed by the definition of stochastic convergence appear to be valid for regional high-skilled employment rates.

For regional total employment rates, the findings provide evidence of the existence of stochastic convergence. The idiosyncratic as well as the common component follow a stationary process. This implies that relative regional employment rates also follow a stationary process. According to these findings, shocks only have transitory effects on the idiosyncratic component and the common component. After a shock, regional total employment rates return back to their steady state. Therefore, disparities in total regional employment rates seem to be mainly characterized by different steady state values. The results provide no evidence that disparities in regional total employment rates occur because of slow or sluggish adjustment processes after a labor market shock.

However, the regional skill-specific employment rates behave differently to the total employment rate. This means that the evolution of regional disparities in total employment rates does not simply reflect the evolution of regional disparities in skill-specific employment rates.

Evidence of stochastic convergence was only found for regional high-skilled employment rates. The idiosyncratic components of regional high-skilled employment rates follow a stationary process and there is one non-stationary common factor with homogeneous factor loadings present in the data. This is in line with the definition of stochastic convergence. In contrast, regional low- and medium-skilled employment rates show divergent behavior.

For regional low-skilled employment rates, the hypothesis of stochastic convergence is clearly rejected. The idiosyncratic components are found to contain a unit root. Therefore, permanent deviations from the common trend are possible on a regional level in the case of low-skilled employment rates. Nevertheless, the evolution of the coefficient of variation did not indicate that the inequality across regions in terms of low-skilled employment rates increased during the last twenty years. One reason might be that the evolution of regional low-skilled employment rates was mainly driven by common movements which overlayed region-specific movements.

In addition, for the regional medium-skilled employment rates, the hypothesis of stochastic convergence has to be rejected. The hypothesis of stochastic convergence allows only for one non-stationary common factor present in the data. However, the $MQ_c^c(m)$ test and the $MQ_f^c(m)$ test indicate that medium-skilled employment rates are characterized by two linear independent common factors which are both $I(1)$. Further, one of the common factors reflecting a slight positive trend in medium-skilled employment is loaded with a different weight in each time series of the panel and, hence, seems to affect the regions differently.

4.6 Conclusion

This chapter deals with the evolution of regional employment disparities within West Germany. It examines the hypothesis of convergence for West German regional employment rates for the time period 1989 to 2008. The number of employees in West Germany was very stable during the last twenty years. However, this period was characterized by a remarkable change of the skill composition of the employees. The number of high-skilled workers increased, while the number of low-skilled workers decreased. Hence, next to regional total employment rates, also regional skill-specific employment rates were investigated to take the changes in the skill composition of employees into account. Skill-specific employment rates were calculated for low-skilled workers, medium-skilled workers and high-skilled workers. Further, to get a comprehensive overview, different approaches to convergence were applied.

Evidence of weak unconditional β-convergence was found for all four employment rates under consideration. However, the negative relationship between the initial values of regional employment rates and their corresponding growth rates implied by the existence of β-convergence does not lead to a decrease in regional inequality. According to the development of the coefficient of variation, the regional dispersion of regional employment rates was stable between 1989 and 2008. One could even observe a rise in the dispersion of the high-skilled employment rate between 1999 and 2003. For regional unemployment rates, the development of the coefficient of variation was characterized by a clear cyclical pattern. In contrast, for regional employment rates, such a cyclical pattern was only hardly observable.

Further, testing the rank-order stability shows that total employment rates were characterized by a small degree of intra-distributional dynamics. Similar results were found for the low- and high-skilled employment rate. In contrast, regional medium-skilled employment rates were characterized by a higher degree of intra-distributional dynamics especially during the 1990s.

Similar to regional unemployment rates, the behavior of regional employment rates can only hardly be characterized by a transition process. Investigating the cross-sectional behavior of regional employment rates shows no evidence of a catching-up process between favorable and unfavorable regions. Hence, also in the case of regional employment rates, the concept of stochastic convergence appears to be more appropriate.

This chapter discussed in detail the restrictions imposed by the definition of stochastic convergence. In the case of stochastic convergence, the idiosyncratic component and the common component of this variable have to follow a stationary process. However, the definition of stochastic convergence is also in line with the existence of one non-stationary common factor with homogeneous factor loadings. Therefore, it is possible to test the hypothesis of stochastic convergence by investigating whether these conditions are valid. For this purpose, the PANIC approach by Bai/Ng (2004) can be applied. Following this alternative way to test the hypothesis of stochastic convergence provides some advantages compared to the traditional way of calculating deviations of regional variables from their national counterpart and examining whether these deviations follow a stationary process.

The results for the total employment rate provide evidence of stochastic convergence. The idiosyncratic component as well as the common component present in regional total employment rates are found to be stationary. Hence, differences in regional total employment rates seem to be the result of different steady state values rather than weak and sluggish adjustment processes after a region-specific shock.

However, in the case of skill-specific employment rates, evidence of stochastic convergence was only found for regional high-skilled employment rates. The hypothesis of stochastic convergence was rejected for regional low-skilled employment rates and regional medium-skilled employment rates.

In the case of the low-skilled employment rate, non-stationarity of the idiosyncratic component is identified as a source of divergence. This means that region-specific shocks have long-lasting effects on regional low-skilled employment and might lead to a permanent deviation from the common trend. The studies by Decressin/Fatás (1995) and Kunz (2012) identify labor mobility as the major adjustment mechanism after a regional labor market shock in the long run for West German regions. Compared to the high-skilled employees, the low-skilled employees are less mobile. This could be one explanation for the long-lasting effects of a shock in the case of low-skilled employment and for temporary effects in the case of high-skilled employment.

The results for the medium-skilled employees are less clear and hard to interpret. The panel unit root tests for the idiosyncratic component lead to ambiguous results. However, two non-stationary common factors were identified for regional medium-skilled employment rates and this is not in line with the definition of stochastic convergence. The medium-skilled workers are the largest group of employees and contain a wide range of different occupations. This stronger heterogeneity within the group of medium-skilled workers compared to other qualification groups might be a possible explanation for these findings.

The change of the skill-composition of employees is usually explained by the so called skill-biased technological change. The technological progress favors high-skilled employment whereas jobs for low-skilled workers get lost. Autor/Levy/Murnane (2003) and Goos/Manning (2007) introduce a more nuanced definition of skill-biased technological change. They emphasize the role of tasks rather than the qualification level of an employee. According to their point of view, the skill-biased technological change leads to diminishing relevance of routine tasks, while the relevance of non-routine tasks becomes more important. Hence, this form of skill-biased technological change does not only take place between high and low-skilled employees, but also within different qualification groups. The empirical results by Spitz-Oener (2006) support this point of view for West Germany. Note, that the ranking of the regions according to the medium-skilled employment rate appears less stable during the last twenty years compared to the other employment rates. Further, one of the common factors identified for medium skilled appears to reflect the slight positive trend in medium-skilled employment. However, each region is affected differently by this common factor because it is characterized by heterogeneous factor loadings. Hence, the impact of the skill-biased technological change might differ for the medium-skilled employees on a regional level, depending on the task composition of the medium-skilled workers.

Only little is known about the role of heterogeneous employment groups and the evolution of regional labor market disparities. This study shows that analyzing the evolution of regional labor market disparities by investigating total employment only provides limited insights. Employment subgroups can behave in a different way to total employment. The changes in the skill competition does not seem to affect the geographical distribution of employment prospects for total employment. However, it seems to go hand in hand with a redistribution of skill-specific employment prospects across regions.

The results indicate that regional total employment rates do not show stochastic convergence because the skill-specific employment subgroups show convergent behavior. Hence, to get a complete picture about the evolution of regional labor market disparities, a more detailed look on employment subgroups is necessary. They appear to be an important driving force for the differences between regions.

Chapter 5

5 Regional labor market dynamics after a labor demand shock

According to the results of the previous chapters, region-specific labor market shocks appear to be an important driving force for persistent regional labor market disparities. This raises the following questions: How long does it take until everything returns back to normal after a regional labor market shock? What are the main adjustment mechanisms after a region-specific labor market shock and how do they work? This chapter analyzes regional labor market dynamics after a region-specific labor demand shock for West German regions and provides additional results for Germany as a whole.

In their seminal paper, Blanchard/Katz (1992) provide an empirical framework with which it is possible to investigate regional adjustment processes after a region-specific labor demand shock. Suppose a person looses his or her job due to an unfavorable regional labor demand shock. This person can either leave the labor force, become unemployed in the region of residence, or move to another region. In an analogous manner, newly created jobs after a positive labor demand shock can either be filled by people out of the labor force, unemployed or people from outside the region. Therefore, the existing literature considers mobility of labor between these different labor market states as the main adjustment mechanism after regional labor market shocks. Blanchard/Katz (1992) suggest a vector autoregressive (VAR) model that considers the interactions between these different states.

By now, many studies exist which adopt or augment the original approach suggested by Blanchard/Katz (1992). Results for West Germany are presented by Decressin/Fatás (1995) and Kunz (2012). Decressin/Fatás (1995) examine adjustment processes for West German federal states and the time period 1975 to 1987. Kunz (2012) examines the adjustment process for West German federal states and the smaller districts for the time period 1989 to 2004. Both studies find for the federal states that in the first year of the shock, the main part of the shock is absorbed by participation decisions and changes in unemployment. The participation rate and the unemployment rate quickly return back to their initial value and very soon migration becomes the main adjustment channel. For the West German districts, Kunz (2012) identifies migration as the most important adjustment mechanism even in the early stages of the shock.

However, it should be kept in mind that in the framework by Blanchard/Katz (1992) migration is the only form of labor mobility. This means that a person can only work in his or her region of residence. This appears to be a very restrictive assumption because commuting as an additional form of labor mobility is excluded.

Therefore, an analysis based on the framework by Blanchard/Katz (1992) runs the risk of overestimating the role of migration during the adjustment process if commuting is not negligible. This chapter will show that in this case, the identified response of migration corresponds to the response of labor mobility as a whole. Therefore, it appears to be reasonable to consider the role of labor mobility in more detail and distinguish between migration and commuting. For this purpose, the framework of Blanchard/Katz (1992) is augmented to allow for both migration and commuting.

According to the theoretical model of regional evolutions provided in section 2.2.2, the role of wages during the adjustment process is twofold. An adverse regional labor demand shock should lead to a decline in regional wages. Low wages trigger out-migration of people and in-migration of firms. What happens to regional employment depends on the relative strength and speed of these two effects. The role of wages during the adjustment process was already investigated by Blanchard/Katz (1992) for the US, Debelle/Vickery (1999) for Australia, Choy/Maré/Mawson (2002) for New Zealand, and Leonardi (2004) for Italy. A corresponding analysis for Germany is still missing. This chapter will fill this gap.

The findings of the literature examining the adjustment process after a labor demand shock differs between countries. This is not surprising because of differences in national labor market institutions. However, labor market institutions are only one possible explanation why the existing studies provide different results.

Choy/Maré/Mawson (2002) point out that it is also possible to obtain different results for the adjustment processes after a labor demand shock even for the same country if regions of different size are considered. This confirms the findings by Kunz (2012) for West Germany which show that labor mobility plays a more important role as an adjustment mechanism in the case of districts compared to federal states. Kunz (2012) points out that labor mobility is more intense between small regional units whereas a lot of migration and commuting activities take place inside large regions. According to the discussion in Choy/Maré/Mawson (2002) and Fredriksson (1999), it is not surprising that labor mobility plays a larger role for small regional units compared to large regional units. In small regional units, fewer labor market opportunities exist. Therefore, after a downturn in regional labor demand, people are more likely to have to look outside their own regions for a new job.

This leads to the question which regional unit is the optimal choice to examine the adjustment processes after a labor demand shock. If regional units are too large, the analysis runs the risk of capturing only a part of the ongoing processes. Examining small regional units such as districts or municipalities, increases the risk of neglecting spatial dependencies because functional labor markets extend across administrative borders. A lot of commuting activities on the district level take place between cities and their hinterland. Suppose someone moves from the city into a rural neighboring district of the city but still works in the city. In this case, changes in labor mobility are not the result of changes in employment opportunities. Hence, for small regional units, the relationship between labor mobility and employment opportunities appears to be ambiguous.

Because of these arguments, the delimitation of regions to analyze the adjustment process after a labor demand shock should reflect the distribution of economic activity in space and the units of analysis should be regarded as economically independent respectively. Therefore, a functional delimitation of regional labor markets appears to be most appropriate. As in chapter 4, the regional planning units provided by the BBSR serve to delineate functional labor markets. The BBSR divides Germany into 96 regional planning units where the city of Hamburg, Bremen and Berlin represent own regional planning units. As discussed in the previous chapter, this would not be in line with the idea of functional labor markets. Therefore, the regional planning units "Schleswig-Holstein Sued", "Hamburg-Umland-Sued", and "Hamburg" are aggregated to the analysis region "Hamburg" as well as "Bremen-Umland" and "Bremen" to the analysis region "Bremen" and "Havelland-Fläming", "Oderland-Spree" and "Berlin" to the analysis region "Berlin". This leads to the 91 German regional planning units used here.

Usually, the main concern when analyzing regional labor market dynamics after a region-specific labor demand shock is not the response of a certain region, but to get information about the adjustment processes of the representative or average region. For this purpose, the regions are pooled in the VAR. This leads to a panel vector autoregressive (PVAR) model.

Each equation of the VAR contains lagged values of the endogenous variable on the right hand side. Hence, after pooling the data, each equation of the PVAR has a dynamic panel specification. This has to be taken into account when estimating the PVAR. Almost every existing study applies a least square dummy variable (LSDV) estimator to estimate the coefficients of the PVAR. However, this estimator only leads to consistent results if the time dimension gets large (see, for example, Nerlove 1967, 1971 and Nickell 1981). In this case, large means that the time dimension of the panel should exceed the value of 30 (see, for example, the simulation results in Judson/Owen 1999). Note, the literature review in section 2.2 shows that this is not the case for most of the existing studies. The panel in this chapter is characterized by a large cross-sectional dimension and a small time dimension. Hence, results from a LSDV estimation are subject to potential bias. Binder/Hsiao/Pesaran (2005) provide several estimators for a PVAR with a large cross-sectional dimension and a small time dimension. Mutl (2009) augments the framework by Binder/Hsiao/

Pesaran (2005) by allowing for spatial correlation of the error terms. Here, the estimation procedure by Mutl (2009) is applied to take the structure of the panel into account.

The remainder of this chapter is as follows. The first section introduces the empirical framework. It augments the original approach provided by Blanchard/Katz (1992) allowing for both commuting and migration. The adjustment process is usually visualized by impulse response functions. This analytical tool is also introduced in section 5.1. Furthermore, the PVAR estimator provided by Mutl (2009) is discussed. Section 5.2 describes the underlying data and provides some stylized facts about the regional variables considered in the analysis. Further, the relationship between regional employment prospects and labor mobility is investigated. Section 5.3 presents the results and section 5.4 concludes.

5.1 Empirical framework

This section introduces the empirical framework applied in this study. The model suggested by Blanchard/Katz (1992) is based on identity (2.45). Section 5.1.1 shows that this identity only provides an adequate framework to examine regional labor market dynamics after a region-specific labor demand shock if there is no commuting activity. Further, a more common identity is derived taking migration and commuting activity into account. The different PVAR specification examined in this study are presented in section 5.1.2. Finally, impulse response analysis and the PVAR estimator suggested by Mutl (2009) are discussed.

5.1.1 Basic principles of the empirical framework

The specification of vector autoregressive (VAR) models to examine the adjustment processes after a regional labor demand shock is based on the following identity (see also section 2.2.4):

$$\text{employment} = (1 - \text{unemployment rate}) \times \text{participation rate} \times \text{population} \qquad (5.1)$$

Identity (5.1) is interpreted in the following way: changes in labor demand trigger changes in unemployment, changes in labor force participation and changes of the population due to migration.

Section 2.2.4 already showed that identity (5.1) is based on a decomposition of the employment rate (see also Rowthorn/Glyn 2006). This section will show that the decomposition of the employment rate only leads to identity (5.1) if the employees working in a region are identical to the employees living in this region. This restriction implies that there is no commuting activity between the regions. People can only start working in a region after moving into this region (if they do not already live there). Labor mobility between regions only takes place via migration and commuting as an additional form of labor mobility is excluded. If this assumption does not hold, commuting activities might also serve as an adjustment mechanism. In this case, an empirical model based on identity (5.1) is misspecified. It no longer provides an adequate framework to analyze the adjustment processes after a labor demand shock because it only captures a part of the ongoing adjustment processes. More precisely, the empirical models applied in previous studies based on identity (5.1) tend to overestimate the response of migration if commuting activities between regions are not negligible. The identified impact of the shock on migration rather reflects the response of labor mobility as a whole. Hence, this section provides an identity that accounts for commuting activities and overcomes this drawback.

The employment rate corresponds to the share of the working age population in a country or region that is employed and is calculated in the following way:

$$\text{employmentrate} = \frac{E^{por}}{POP} \tag{5.2}$$

where POP denotes the working age population and E^{por} denotes employment measured by place of residence. This means E^{por} corresponds to the number of employees that live in the region under consideration. Note, that this index is suppressed in identity (5.1). Thus, the decomposition of the employment rate has to be expressed as follows:

$$\frac{E^{por}}{POP} = \frac{E^{por}}{LF} \times \frac{LF}{POP} \tag{5.3}$$

where LF denotes the labor force that corresponds to the sum of the employees measured by place of residence and the unemployed U. Solving equation (5.3) for E^{por} leads to:

$$E^{por} = \frac{E^{por}}{LF} \times \frac{LF}{POP} \times POP \tag{5.4}$$

where E^{por}/LF corresponds to the labor force employment rate and LF/POP corresponds to the participation rate. Further transformation of the labor force employment rate is necessary to rewrite identity (5.4) in terms of the unemployment rate:

$$
\begin{aligned}
E^{por} &= \frac{E^{por}}{U+E^{por}} \times \frac{LF}{POP} \times POP \\
E^{por} &= \frac{E^{por}+U-U}{U+E^{por}} \times \frac{LF}{POP} \times POP \\
E^{por} &= \left(1-\frac{U}{U+E^{por}}\right) \times \frac{LF}{POP} \times POP \\
E^{por} &= \left(1-\frac{U}{LF}\right) \times \frac{LF}{POP} \times POP
\end{aligned}
\tag{5.5}
$$

where U/LF corresponds to the unemployment rate. According to identity (5.5), changes in employment measured by place of residence, triggers changes in unemployment, changes in labor force participation and changes in the working age population due to migration. However, this is not the relationship we are really interested in when analyzing the adjustment processes after a labor demand shock. Employment measured by place of residence is a variable that represents regional labor supply rather than regional labor demand. Strictly speaking, identity (5.1) represents a suitable framework to examine regional labor market dynamics after a labor supply shock but not to investigate regional labor market dynamics after a regional labor demand shock.

Regional labor demand is determined by the firms that are located in a region. Hence, the appropriate measure for regional labor demand is the number of employees working in this region.[1] Let E^{pow} denote employment measured by place of work. Augmenting equation (5.4) by this labor demand measure leads to the following expression:

$$
E^{por} \times E^{pow} = \left(\frac{E^{por}}{LF}\right) \times \left(\frac{LF}{POP}\right) \times POP \times E^{pow} \tag{5.6}
$$

Equation (5.6) can be rewritten as:

$$
E^{pow} = \left(\frac{E^{por}}{LF}\right) \times \left(\frac{LF}{POP}\right) \times POP \times \left(\frac{E^{pow}}{E^{por}}\right) \tag{5.7}
$$

Equation (5.7) can also rewritten in terms of the unemployment rate:

$$
E^{pow} = \left(1-\frac{U}{LF}\right) \times \left(\frac{LF}{POP}\right) \times POP \times \left(\frac{E^{pow}}{E^{por}}\right) \tag{5.8}
$$

1 Indeed, the existing studies about regional labor market dynamics apply employment data measured by place of work. Only Kunz (2012) provides results for an innovation in employment measured by place of work and by place of residence.

Identity (5.8) differs form identity (5.1) by an additional term on the right hand side that corresponds to the ratio of employment measured by place of work and employment measured by place of residence. Only if the employees that work in the region are identical to the employees that live in the region does the ratio of these two variables become unity. In this special case, identity (5.1) and identity (5.8) are identical.

If the number of employees measured by place of work and the number of employees measured by place of residence differ, then this implies that there must be people commuting between the regions. Hence, the ratio between these two variables can be interpreted as a measure for (net) commuting activity.

According to identity (5.8), a change in employment due to a labor demand shock triggers changes in unemployment, changes in labor force participation, changes of the working age population due to migration and changes in the commuting activity.

The assumption of no or negligible commuting activities might be valid for large regional units but appears to be violated for smaller regional units such as districts or counties. In the case of Germany, the assumption of no commuting activities has to be considered as very critical even for larger regional units. Burda/Hunt (2001) point out that for many people in East Germany, commuting has been a feasible substitute instead of leaving their place of residence and moving to West Germany.

5.1.2 Specification of the PVAR

The original VAR applied in Blanchard/Katz (1992) includes the employment growth rate ($\gamma^n_{i,t}$), the logarithm of the labor force employment rate ($le_{i,t}$), and the logarithm of the participation rate ($pr_{i,t}$). The main interest of the study by Blanchard/Katz (1992) is to examine the adjustment processes after a region-specific shock. To account for common movements in the regional variables, all variables enter the VAR as relative regional variables denoted by $\tilde{\gamma}^n_{i,t}$, $\tilde{le}_{i,t}$ and $\tilde{pr}_{i,t}$. This means that these variables are measured relative to their national counterpart. To investigate the adjustment processes after a regional labor demand shock for the average or typical region, Blanchard/Katz (1992) apply the following panel vector autoregressive (PVAR) model:

$$\tilde{\gamma}^n_{i,t} = \alpha_{i10} + \alpha_{11}(L)\tilde{\gamma}^n_{i,t-1} + \alpha_{12}(L)\tilde{le}_{i,t-1} + \alpha_{13}(L)\tilde{pr}_{i,t-1} + \varepsilon^n_{i,t} \tag{5.9}$$

$$\tilde{le}_{i,t} = \alpha_{i20} + \alpha_{21}(L)\tilde{\gamma}^n_{i,t} + \alpha_{22}(L)\tilde{le}_{i,t-1} + \alpha_{23}(L)\tilde{pr}_{i,t-1} + \varepsilon^{le}_{i,t} \tag{5.10}$$

$$\tilde{pr}_{i,t} = \alpha_{i30} + \alpha_{31}(L)\tilde{\gamma}^{n}_{i,t} + \alpha_{32}(L)\tilde{le}_{i,t-1} + \alpha_{33}(L)\tilde{pr}_{i,t-1} + \varepsilon^{pr}_{i,t} \tag{5.11}$$

where i denotes the cross-sectional dimension with $i = 1 \dots N$ and t denotes the time dimension with $t = 1 \dots T$. α refers to the coefficients, (L) denotes the lag operator and error terms are denoted by $\varepsilon^{n}_{i,t}$, $\varepsilon^{le}_{i,t}$ and $\varepsilon^{pr}_{i,t}$. Further, region-specific constant terms are included in each equation to control for regional fixed effects.

Based on the estimated coefficients of this system of equations, Blanchard/Katz (1992) derive the responses of the employment level, the unemployment rate, the participation rate and migration after a labor demand shock. Because only the participation rate enters the PVAR directly, further transformations are necessary to obtain the effects of the labor demand shock on the other three measures.

The development of the employment level after a labor demand shock can easily be calculated based on the regression results of the relative regional employment growth rate $\tilde{\gamma}^{n}_{i,t}$. To examine the response of the unemployment rate due to a labor demand shock, Blanchard/Katz (1992) apply the relationship $\log le_{i,t} = \log(1 - ur_{i,t}) \approx -ur_{i,t}$.

To derive the impact of the shock on migration, identity (5.7) can be used. However, identity (5.7) is written in terms of the employment level whereas the PVAR is specified in terms of the employment growth rates. Hence, we also need to rewrite the identity in terms of growth rates to use it to derive the response of migration to the shock:[2]

$$\gamma E^{pow} = \gamma\left(\frac{E^{por}}{LF}\right) + \gamma\left(\frac{LF}{POP}\right) + \gamma\left(\frac{E^{pow}}{E^{por}}\right) + \gamma POP \tag{5.12}$$

Blanchard/Katz (1992) assume that there is no commuting activity between the regions and the employees measured by place of residence and employees measured by place of work are identical. This means $E^{pow} = E^{por} = E$ and identity (5.12) reduces to:

2 The first difference of a variable measured in logarithms corresponds to the growth rate of this variable ($\Delta(\log x) = \Delta x / x$). This relationship is used here to derive identity (5.12) from identity (5.7). Taking the logarithm from identity (5.7) leads to:

$$\log E^{pow} = \log\left(\frac{E^{por}}{LF}\right) + \log\left(\frac{LF}{POP}\right) + \log\left(\frac{E^{pow}}{E^{por}}\right) + \log POP$$

Then, fist differences are taken that leads to an expression of identity (5.7) in terms of growth rates instead of levels given by:

$$\Delta\log E^{pow} = \Delta\log\left(\frac{E^{por}}{LF}\right) + \Delta\log\left(\frac{LF}{POP}\right) + \Delta\log\left(\frac{E^{pow}}{E^{por}}\right) + \Delta\log POP$$

or rewritten as follows:

$$\frac{\Delta E^{pow}}{E^{pow}} = \frac{\Delta(E^{por}/LF)}{(E^{por}/LF)} + \frac{\Delta(LF/POP)}{(LF/POP)} + \frac{\Delta(E^{pow}/E^{por})}{(E^{pow}/E^{por})} + \frac{\Delta POP}{POP}$$

$$\gamma E = \gamma\left(\frac{E}{LF}\right) + \gamma\left(\frac{LF}{POP}\right) + \gamma(POP) \tag{5.13}$$

In this case, the impact of the shock on migration can be derived using the following identity:[3]

$$\gamma(POP) = \gamma E - \gamma\left(\frac{E}{LF}\right) - \gamma\left(\frac{LF}{POP}\right) \tag{5.14}$$

The PVAR applied here differs from the system of equations suggested by Blanchard/Katz (1992) in several ways. The PVAR takes the following form:

$$x_{i,t} = A(L)x_{i,t-1} + u_{i,t} \tag{5.15}$$

where $x_{i,t}$ denotes the vector of endogenous variables, A denotes the matrix of regression coefficients, and $u_{i,t}$ is a vector of disturbance terms. The disturbance term is assumed to follow a two-way error component structure including regional fixed effects to take unobserved regional heterogeneity into account. Further, the disturbance terms of the cross-sectional units in the PVAR are allowed to be spatially dependent. These assumptions are discussed in detail in section 5.1.4.

Note, that in equation (5.15), the right hand side variables are identical in each equation. In contrast, in the original VAR by Blanchard/Katz (1992) the current values of the relative regional employment growth rate are included in the labor force employment rate equation and the participation rate equation. Hence, the PVAR in this chapter is more in line with the specifications provided in Jimeno/Bentolila (1998), Fredriksson (1999), Mäki-Arvela (2003), and Leonardi (2004).

The analysis starts with the three variable model suggested by Blanchard/Katz (1992). The vector of endogenous variables of this PVAR is given by:

$$x'_{i,t} = [\tilde{\gamma}^{n}_{i,t}, \tilde{le}_{i,t}, \tilde{pr}_{i,t}] \tag{5.16}$$

where $\tilde{\gamma}^{n}_{i,t}$ denotes the growth rate of the number of employees measured by place of work, $\tilde{le}_{i,t}$ denotes the logarithm of the labor force employment rate, and $\tilde{pr}_{i,t}$ is the logarithm of the participation rate (all variables measured as relative regional variables). The impact of a labor demand shock on labor mobility can be derived using identity (5.12):

$$\gamma\left(\frac{E^{pow}}{E^{por}}\right) + \gamma POP = \gamma E^{pow} - \gamma\left(\frac{E^{por}}{LF}\right) - \gamma\left(\frac{LF}{POP}\right) \tag{5.17}$$

3 Note, only if the assumption of no commuting activity holds and $E^{pow} = E^{por} = E$ is it possible to determine the response of migration due to a labor demand shock using this identity. Otherwise, the identity provides the response of labor mobility overall including migration and commuting.

Hence, the three variable approach only provides information about the response of labor mobility as a whole to a shock in regional labor demand. It is not possible to distinguish between commuting and migration. To disclose the effect of a regional labor demand shock on migration and commuting, it is necessary to augment the vector of variables given in equation (5.16). Let $ca_{i,t}$ denote net-commuting activity in region i at time t that corresponds to the ratio of the number of employees measured by place of work and the number of employees measured by place of residence. The corresponding growth rate is given by $\gamma_{i,t}^{ca}$. The vector of endogenous variables of the PVAR augmented by this additional variable measured as a relative regional variable can be expressed as:

$$x_{i,t}' = [\tilde{\gamma}_{i,t}^{n}, \tilde{l}e_{i,t}, \tilde{p}r_{i,t}, \tilde{\gamma}_{i,t}^{ca}] \tag{5.18}$$

Identity (5.12) can be applied to derive the effect of a regional labor demand shock on migration based on the results of this PVAR:

$$\gamma POP = \gamma E^{pow} - \gamma\left(\frac{E^{por}}{LF}\right) - \gamma\left(\frac{LF}{POP}\right) - \gamma\left(\frac{E^{pow}}{E^{por}}\right) \tag{5.19}$$

However, changes in net-commuting activity allow no straightforward interpretation about the origin of a rise or fall of regional commuting activity. For example, an increase of net-commuting activity goes hand in hand with a rise of in-commuters, while the number of out-commuters remains stable as well as with a decreasing number of out-commuters, while the number of in-commuters remains stable. Only in the first case does a rise in net-commuting reflect a rise in labor mobility.

There are two possible ways how commuting can serve as an adjustment channel. New jobs after a positive labor demand shock can either be filled by in-commuters from outside the region, or by former out-commuters that now stay in the region. The responses of in-commuters and out-commuters to an innovation in regional labor demand do not necessarily have to be symmetric. Commuting is costly because of travel costs and external effects. For former out-commuters, these costs of commuting fall away if they start to work in their region of residence. Hence, out-commuters might be more likely to accept a job offer in their region of residence and lower wages compared to workers living outside the region. In contrast, for workers living outside the region, commuting is only attractive if the costs of commuting are compensated by higher wages. Following this discussion, one would expect the response of out-commuters after a regional labor demand shock to exceeds the response of the in-commuters.

In contrast, this has not to be the case if employment is heterogenous and the regional labor demand shock is selective in terms of different employment subgroups. For example, if new jobs favor workers with a certain qualification level or human capital that the workers living in the region can not provide, one could also expect the response of the in-commuters to exceed that of the out-commuters. Hence, introducing gross-commuting flows into the model, can provide additional information about labor mobility and the nature of the shock.

Let $ic_{i,t}$ denote the number of in-commuters in region i at time t, and let $oc_{i,t}$ denote the corresponding measure for the number of out-commuters. The growth rates for these two measures are given by $\gamma^{ic}_{i,t}$ and $\gamma^{oc}_{i,t}$. The vector of endogenous variables of the PVAR including relative regional gross-commuting flows is given by:

$$x'_{i,t} = [\tilde{\gamma}^{n}_{i,t}, \tilde{l}e_{i,t}, \tilde{p}r_{i,t}, \tilde{\gamma}^{oc}_{i,t}, \tilde{\gamma}^{ic}_{i,t}] \tag{5.20}$$

According to the theoretical model of regional evolution introduced by Blanchard/Katz (1992), the response of wages after a labor demand shock affects the speed of adjustment. However, the role of wages during the adjustment process is twofold. For example, lower wages because of an adverse shock induce net in-migration of firms and the creation of new jobs. Lower wages and higher unemployment induce net out-migration of labor. The long-run effect on employment depends on the relative strength and speed of the two effects. Hence, it seems to be reasonable to examine the role of the wage feedback during the adjustment process.

Let $wa_{i,t}$ denote wages per employee in region i at time t. Following Choy/Maré/Mawson (2002), the growth rate of wages per employee $\gamma^{wa}_{i,t}$ is considered in the PVAR. The vector of endogenous variables for the three variable model suggested by Blanchard/Katz (1992) augmented by the growth rate of wages per employee is given by:

$$x'_{i,t} = [\tilde{\gamma}^{n}_{i,t}, \tilde{\gamma}^{wa}_{i,t}, \tilde{l}e_{i,t}, \tilde{p}r_{i,t}] \tag{5.21}$$

Again, all variables enter the PVAR as relative regional variables. For the model including net-commuting, the corresponding vector of endogenous variables augmented by the growth rate of regional wages per employee $\tilde{\gamma}^{wa}_{i,t}$ is given by:

$$x'_{i,t} = [\tilde{\gamma}^{n}_{i,t}, \tilde{\gamma}^{wa}_{i,t}, \tilde{l}e_{i,t}, \tilde{p}r_{i,t}, \tilde{\gamma}^{ca}_{i,t}] \tag{5.22}$$

For the model including gross-commuting, the corresponding vector of endogenous variables is given by:

$$x'_{i,t} = [\tilde{\gamma}^{n}_{i,t}, \tilde{\gamma}^{wa}_{i,t}, \tilde{l}e_{i,t}, \tilde{p}r_{i,t}, \tilde{\gamma}^{oc}_{i,t}, \tilde{\gamma}^{ic}_{i,t}] \tag{5.23}$$

Note, that the ordering of the variables implies that a current change in regional employment affects regional wages but not vice versa. This identification assumption is appealing because the aim of this chapter is to examine the effects of a regional labor demand shock rather than the effects of a regional wage shock.

5.1.3 Impulse response analysis

It is hard to assess the interaction among the variables in the PVAR solely on the basis of the estimated coefficients. In general, the effect of an impulse in one variable and the corresponding responses of the other variables are depicted graphically based on impulse response functions. This makes it possible to get a visual impression of the dynamics after an innovation in labor demand.

The regional evolution literature is interested in tracing the responses of the system of equations after an impulse in labor demand. The easiest way to examine what happens to the system after an innovation in labor demand is to assume that there is a one period increase in the employment growth rate and that no further shock in the other variables occurs at that date. However, this assumption imposes the restriction that a shock in one variable is not accompanied by responses of the other variables at least in the period of the shock. This appears to be a very unrealistic assumption when investigating adjustment processes after a labor demand shock. The creation of new jobs after a positive innovation in labor demand must go hand in hand with changes in unemployment, labor force participation or labor mobility. Otherwise, these new jobs could not be filled. Therefore, a labor demand shock in one period has to trigger contemporaneous changes in at least another variable at the same time. Hence, it appears to be appropriate to relax the assumption that the effects of a shock on different variables are independent. In this case, it has to be assured that the responses of the system are the effect of a shock in labor demand and do not reflect an innovation in the other variables.

Blanchard/Katz (1992) take this problem into account by the specification of the VAR. Note, that in their VAR, the current value of the relative regional employment growth rate $\tilde{\gamma}^{n}_{i,t}$ enters the labor force employment rate equation and the participation rate equation. In contrast, current changes in the labor force employment rate and the participation rate are not allowed to affect the other variables in the system. Because of this identification assumption, a shock in the relative regional employment growth rate is accompanied by immediate changes in all other variables in the VAR. Further, this identification assumption assures that the response in the variables are solely triggered by a change in labor demand and not by the supply side factors entering the VAR.

Here, another identification strategy is applied to trace the effects of a labor demand shock. This study follows Jimeno/Bentolila (1998), Fredriksson (1999), and Leonardi (2004) and applies so called orthogonalized impulse response functions.

Lets consider a VAR of order p including m equations of the following form:

$$x_t = \sum_{k=1}^{p} A_k x_{t-k} + u_t \tag{5.24}$$

where x_t denotes the vector of variables, A_k denotes the coefficient matrix and the error term u_t is a white noise process. The impulse response function does not depend on the cross-sectional dimension of the panel. Hence, the subscript i is omitted here. The interests of impulse response analysis is the variation of the variables around their means. Therefore, the mean term is suppressed in equation (5.24). The impulse response function is based on the infinite moving average (MA) representation of the VAR of order p:

$$x_t = \sum_{k=0}^{\infty} \Phi_k u_{t-k} \tag{5.25}$$

where Φ_k denotes the coefficient matrix. According to equation (5.25), the current value of the variables results from past shocks weighted by Φ_k. Therefore, the elements of Φ_k reflect the responses of the system to a shock. It is possible to compute Φ_k recursively based on the coefficient matrix of equation (5.24) using $\Phi_0 = I_m$ and $\Phi_k = \sum_{j=1}^{k} \Phi_{k-j} A_j$ where $A_j = 0$ for $j > p$ (see, for example, Lütkepohl 2005).

However, equation (5.25) provides impulse response functions under the restriction that shocks in different equations of the VAR are independent. Orthogonalized impulse response functions can be applied to relax this restriction. The idea of orthogonalized impulse response functions is to modify equation (5.25) so that the residuals are orthogonal this means uncorrelated. After this transformation, it is possible to refer the common part of an innovation in one variable to the other variables of the system (see, for example, Lütkepohl 2005).

This is obtained be the Cholesky decomposition of the variance covariance matrix Σ_u of the error terms that is given by $\Sigma_u = PP'$. P is a lower triangular nonsingular matrix with positive diagonal elements. Equation (5.25) can be rewritten as:

$$x_t = \sum_{k=0}^{\infty} \Phi_k P P^{-1} u_{t-k} = \sum_{k=0}^{\infty} \Theta_k \varepsilon_{t-k} \tag{5.26}$$

where $\Theta_k = \Phi_k P$ and $\varepsilon_t = P^{-1} u_t$ is a white noise process. The variance covariance matrix of ε_t is given by:

$$\Sigma_{\varepsilon} = P^{-1}\Sigma_{u}(P^{-1})' = I_{K} \tag{5.27}$$

As equation (5.27) shows, the white noise errors ε_t have uncorrelated components. This means they are orthogonal to each other. Therefore, it is reasonable to assume for equation (5.26) that an innovation in one component of ε_t does not go in hand in hand with innovations in the other components of ε_t. This allows us to trace the effects of an isolated labor demand shock. Hence, it is assured that changes occurring in the other variables of the system solely reflect the responses of the system to this impulse and are not the result of an additional shock. The modified coefficient matrix Θ_k is interpreted as the responses of the system according to this orthogonalized impulse.

Because $\Theta_k = \Phi_k P$ and $\Phi_0 = I_m$, the impulse in the initial period corresponds to P. This means that the initial innovation is derived by the Cholesky decomposition of the variance covariance matrix Σ_u. The response in the period after the shock is given by Θ_1 which can be computed as $\Theta_1 = \Phi_1 P = \Phi_0 A_1 P = I_m A_1 P$. The response of the system for the following periods can be computed in a similar way (depending on the order of the VAR).

Further, equation (5.27) indicates that the residuals ε_t have unit variance. Thus, a simulated shock occurring in the system corresponds to a one standard deviation innovation.

The triangularity of matrix ε_t implies that a shock in one variable has a contemporaneous effect on all the variables following in the VAR but not vice versa. Hence, the ordering of the variables is an important issue when applying orthogonalized impulse response functions (see, for example, Lütkepohl 2005). The first variable should be the only one with a potential impact on the other variables entering the VAR but not vice versa. This chapter examines the effect of a region-specific labor demand shock. Hence, it is assumed that changes in regional employment growth trigger changes in the other variables. The ordering of the other variables corresponds to the set of endogenous variables of the different models described in section 5.1.2.

5.1.4 Estimation strategy

The region evolution literature is usually interested in the response of the average region to a labor demand shock. For this reason, all regions are pooled together which leads to a panel vector autoregressive (PVAR) model. Usually, region-specific constant terms are included in each equation to allow for regional fixed effects. Then, the majority of the studies apply an ordinary least squares (OLS) estimator to the multi equation system.[4] This procedure corresponds to estimating the coefficients of the PVAR by a least squares dummy variable (LSDV) estimator. However, such a LSDV estimator in a dynamic panel framework where lagged values of the endogenous variable enter the right hand side of the regression is subject to bias if the time dimension of the panel is small (see, for example, Nerlove 1967, 1971 and Nickell 1981).

Note, that the results derived by the LSDV estimator are exactly identical to the results obtained after taking deviations from cross-sectional means to eliminate the fixed effects and applying OLS on this transformed regression (see, for example, Arellano 2003).[5] This procedure corresponds to the so called within-group (WG) estimator. It can be shown for a dynamic panel model that after the within transformation, the transformed values of the lagged endogenous variable are correlated with the transformed error term. Therefore, the assumption of strict exogeneity is no longer valid for the lagged endogenous variable after this transformation. The transformed regression equation suffers an endogeneity problem. As a consequence, the regression coefficients derived by the WG estimator and, hence, by the LSDV estimator are inconsistent for a fixed time dimension even if the cross-sectional dimension tends to infinity (for more details see, for example, Arellano 2003). Nickell (1981) analytically derived this bias and shows that the bias disappears if the time dimension tends to infinity. The simulation results by Judson/Owen (1999) suggest that a time dimension of more than 30 observations can be considered as sufficient to overcome this so called Nickell bias. However, the panel in this study is characterized by a large cross-sectional dimension and a small time dimension. Hence, the results might be subject to the Nickell bias if a LSDV estimator is applied. The estimation strategy has to take this into account.

For a single equation dynamic panel model characterized by a large cross-sectional dimension and a small time dimension, usually generalized method of moments (GMM) estimators (see, for example, Arellano/Bond 1991, Arellano/Bover 1995, Ahn/Schmidt 1995, Blundell/Bond 1998) are applied to overcome the Nickell bias. Binder/Hsiao/Pesaran (2005) develop a quasi maximum likelihood (QML) estimator for a PVAR and generalize GMM estimation to a system context. The estimators provided by Binder/Hsiao/Pesaran (2005) do not need the assumption that both the cross-sectional dimension and the time dimension are large. Hence, they can applied to panel data with a small time dimension.

Here, the fixed effects QML estimator is applied because it provides several advantages compared to the various GMM approaches. The simulation results by

4 One exception is Fredriksson (1999), who applies the mean group estimator suggested by Pesaran/Smith/Im (1996).

5 Of course, except for the fixed effects.

Binder/Hsiao/Pesaran (2005) show that the fixed effects QML estimator tends to outperform the several GMM estimators in finite samples under both normal and non-normal errors. Further, even in a panel with a short time dimension, the underlying data could have arisen from non-stationary and/or co-integration processes. It is well known that the standard GMM approach by Arellano/Bond (1991) breaks down if the endogenous variable follows a non-stationary process (see, for example, the discussion in Arellano 2003). Arellano/Bond (1991) suggest taking first-differences to eliminate the fixed effects and using lagged level variables as instruments for the first-differenced form of the model. In the case of non-stationarity, the moment conditions no longer hold and the GMM estimator will become inconsistent. The extended GMM estimators provided by Arellano/Bover (1995), Ahn/Schmidt (1995), and Blundell/Bond (1998) overcome this problem by proposing an additional set of moment conditions. However, these conditions require the assumption that the individual effects and the disturbances are uncorrelated. The simulation results in Binder/Hsiao/Pesaran (2005) show that the precision of these GMM estimators deteriorates if the strength of the correlation relationship between these two measures increases. Binder/Hsiao/Pesaran (2005) argue that it is possible to solve this problem by reformulating the standard GMM approach using lagged values of the variables in first-differences as instruments. However, they also point out that in the case of a stationary process, the correlation between the variables in first differences is only small. Hence, results from this GMM approach might be highly inefficient. In contrast to the GMM estimators, the QML estimator does not suffer from these problems.

Mutl (2009) extends the PVAR literature to allow for spatial dependence of the error terms of the model. He follows the spatial econometrics literature and studies a first order spatial autocorrelation model with a known spatial weighting matrix. If the disturbance terms follow a spatial autoregressive process, this implies that the region under consideration is affected by shocks in neighboring regions. Hence, an innovation in labor demand can also be triggered via regional spillover effects. Controlling for spatial correlation in the disturbance term assures that the disturbances are free from such spillover effects. This makes it possible to trace the effects of a region-specific shock in labor demand.

Let $x_{i,t}$ be the $m \times 1$ vector of m endogenous variables for the ith cross-sectional unit, with $i = 1 \ldots N$ and t refers to the time dimension, with $t = 1 \ldots T$. Please note, that m also corresponds to the number of different equations in the PVAR. The first order PVAR model[6] for cross-sectional unit i can be written as:

6 The exposition is restricted to a first order PVAR for simplicity.

$$x_{i,t} = Ax_{i,t-1} + u_{i,t} \tag{5.28}$$

where A denotes the matrix of slope coefficients and $u_{i,t}$ is a $m \times 1$ vector of disturbances. The error term $u_{i,t}$ is allowed to be dependent among the cross-sectional units and is given by:

$$u_{i,t} = \lambda \sum_{j=1}^{N} w_{i,j} u_{j,t} + (I_m - A)\ {}_{i} + \varepsilon_{i,t} \tag{5.29}$$

where $w_{i,j}$ denotes the known spatial weighting parameters describing how "close" the other regions are to the region i. The scalar parameter λ captures the degree of spatial correlation. To determine the proximity of the regions, common borders are used here. $w_{i,j}$ is 1 if regional planning unit i and regional planning unit j share a common border. Otherwise $w_{i,j}$ becomes 0. No region can share a common border with itself. Hence $w_{i,i}$, is always 0. $\varepsilon_{i,t}$ are independent innovations, μ_i represents the individual-specific effects and I_m denotes the identity matrix. According to Binder/Hsiao/Pesaran (2005) and Mutl (2009) the reason for restricting the individual-specific effects to the form $(I_m - A)\mu_i$ is to assure that in the case of a unit root in the model, the trend behavior is the same as in the stationary case. Note, model (5.28) contains m equations. Hence, the observations $x_{i,t-1}$, the individual-specific effects μ_i, and the disturbances $u_{i,t}$ and $\varepsilon_{i,t}$ are $m \times 1$vectors and the spatial weighting matrix $w_{i,j}$, the matrix of slope coefficients A and the identity matrix are matrices of size $m\,x\,m$.

Stacking across individuals leads to the following expression:

$$x_t = (I_N \otimes A)x_{t-1} + u_t$$

$$u_t = \lambda W u_t + [I_N \otimes (I_m - A)]\mu + \varepsilon_t \tag{5.30}$$

where x_t, μ, u_t and ε_t are all vectors of size $mN \times 1$ with $x_t = (x'_{1t} \dots x'_{Nt})'$, $\mu_t = (\mu'_{1t} \dots \mu'_{Nt})'$, $u_t = (u'_{1t} \dots u'_{Nt})'$ and $\varepsilon_t = (\varepsilon'_{1t} \dots \varepsilon'_{Nt})'$. Following Mutl (2009), the indexation with N is omitted in order to maintain legible notation.

The $mN \times mN$ weighting matrix W is:

$$W = \begin{pmatrix} w_{11} & \cdots & w_{1N} \\ \vdots & \ddots & \vdots \\ w_{N1} & \cdots & w_{NN} \end{pmatrix}_{mN \times mN} \tag{5.31}$$

Solving for the disturbance term yields:

$$u_t = (I_{mN} - \lambda W)^{-1}([I_N \otimes (I_m - A)]\mu + \varepsilon_t) \tag{5.32}$$

To eliminate the individual-specific effects, first differences are taken. Equation (5.30) in first differences is given by:

$$\begin{aligned} \Delta x_t &= (I_N \otimes A)\Delta x_{t-1} + \Delta u_t \\ \Delta u_t &= (I_{mN} - \lambda W)^{-1}\Delta\varepsilon_t \end{aligned} \tag{5.33}$$

Therefore, the model in first differences is given by:

$$\Delta x_t = (I_N \otimes A)\Delta x_{t-1} + (I_{mN} - \lambda W u_t)^{-1}\Delta\varepsilon_t \tag{5.34}$$

Note, that the disturbance term in equation (5.34) is still spatially correlated. However, the spatial correlation of the error term can be removed by multiplying both sides of equation (5.34) by $(I_{mN} - \lambda W)$. This procedure is called the spatial Cochrane-Orcutt transformation (see, for example, Kelejian/Prucha 1997). After this transformation, equation (5.34) can be rewritten as:

$$(I_{mN} - \lambda W)\Delta x_t = (I_{mN} - \lambda W)(I_N \otimes A)\Delta x_{t-1} + \Delta\varepsilon_t \tag{5.35}$$

If no spatial dependence exists and $\lambda = 0$, equation (5.35) corresponds to a fixed-effect PVAR considered in Binder/Hsiao/Pesaran (2005). In this case, the provided estimators can be applied to get consistent and efficient estimates for the slope coefficients. If spatial correlation among the cross-sectional units exists and $\lambda \neq 0$, these estimators still lead to consistent results. This means that the slope coefficients converge to their true values. However, the estimation results are inefficient. The standard significance test for the regression coefficients are no longer valid and inference becomes misleading.

The spatial autocorrelation parameter is unknown. Hence, consistent estimates for λ are needed for the spatial Cochrane-Orcutt transformation. In turn, consistent estimates for λ require information about the spatially correlated error term u_t. The spatial econometrics literature suggests a three step approach to solve this problem and to get consistent and efficient estimation results for a spatial error model. The appropriate estimator for the model in the case of no spatial dependence in the error term leads to consistent results even if the assumption of no spatial correlation is invalid. This implies that residuals from this estimation can be applied to derive consistent estimates for λ. Therefore, the first step is to apply this estimator to the model and compute the residuals. The second step is to determine λ based on the calculated residuals. The third step consists of the spatial

Cochrane-Orcutt transformation and the estimation of the transformed model. Mutl (2009) provides a similar three-step estimation procedure for the PVAR.

In the first step, an instrumental variable (IV) approach is used to get consistent estimates to calculate the spatially correlated disturbances. Mutl (2009) suggest stacking the model in a different way to derive the IV estimator. After taking transpose and stacking the observations at different times for a given cross-section i, equation (5.33) can be expressed as:

$$\begin{pmatrix} \Delta x'_{i1} \\ \vdots \\ \Delta x'_{iT} \end{pmatrix}_{T\times m} = \begin{pmatrix} \Delta x'_{i0} \\ \vdots \\ \Delta x'_{iT-1} \end{pmatrix}_{T\times m} A'_{m\times m} + \begin{pmatrix} \Delta u'_{i1} \\ \vdots \\ \Delta u'_{iT} \end{pmatrix}_{T\times m} \tag{5.36}$$

In a more compact way, equation (5.36) can be rewritten as:

$$\Delta X_i = \Delta X_{i,-1} A' + \Delta U_i \tag{5.37}$$

Stacking the cross-sections yields to:

$$\Delta X = \Delta X_{-1} A' + \Delta U \tag{5.38}$$

where $\Delta X = (\Delta X'_1, \ldots, \Delta X'_N)'$, $\Delta X_{-1} = (\Delta X'_{1,-1}, \ldots, \Delta X'_{N,-1})'$ and $\Delta U = (\Delta U'_1, \ldots, \Delta U'_N)'$. Mutl (2009) defines the IV estimator of A as :

$$\hat{A}_{IV} = \left[\hat{Z}'\hat{Z}\right]^{-1} \hat{Z}'\Delta X \tag{5.39}$$

where $\hat{Z} = P_H \Delta X$ with $P_H = H(H'H)^{-1}H'$. H is a vector of instruments used for ΔX_{-1}. Mutl (2009) suggests the use of the instruments $H = X_{-2} = (X'_{1,-2}, \ldots, X'_{N,-2})'$ where $X_{i,-2} = (x_{i,-1}, \ldots, x_{i,T-2})'$. The estimates of the spatially correlated disturbances can be derived as:

$$\hat{u}_t = x_t - (I_N \otimes \hat{A}_{IV}) x_{t-1} \tag{5.40}$$

In the second step, Mutl (2009) provides a multivariate version of the spatial generalized moment (GM) estimation procedure to determine a consistent estimator for λ based on the residuals from the IV estimation in the first step. It is possible to express equation (5.29) in the following way:

$$u_{i,t} = \lambda \sum_{j=1}^{N} w_{i,j} u_{j,t} + \nu_{i,t} \tag{5.41}$$

where $\nu_{i,t}$ is given by:

$$\nu_{i,t} = (I_m - A)\mu_i + \varepsilon_{i,t} \tag{5.42}$$

The moment conditions for the spatial GM estimation procedure are derived based on these two equations. For details about the moment conditions for multivariate versions of the spatial GM estimation see Mutl (2009). Kelejian/Prucha (1999) already show consistency of a similar two stage procedure for univariate single cross-section models with spatial lags in both the dependent variable as well as the error term. Kapoor/Kelejian/Prucha (2007) extend the results for an univariate static panel model. Both of these papers consider non-stochastic exogenous variables and, hence, their results are not directly applicable to the PVAR model considered here. However, Mutl (2006) contains a straightforward extension of their proofs for univariate dynamic panel models. Mutl (2009) conjectures that the spatial GM procedure will also be consistent under an appropriate set of assumptions in a multivariate setting.

The third step consists of the spatial Cochrane-Orcutt transformation of the PVAR and the estimation of the transformed model. Let $\hat{\lambda}$ denote the estimated spatial autocorrelation parameter derived in the second step. The PVAR after the spatial Cochrane-Orcutt transformation is given by:

$$(I_{mN} - \hat{\lambda}W)\Delta x_t = (I_{mN} - \hat{\lambda}W)(I_N \otimes A)\Delta x_{t-1} + \Delta\varepsilon_t \tag{5.43}$$

This transformed model can be estimated with standard techniques, such as the QML method or the multivariate extension of GMM approach given in Binder/Hsiao/Pesaran (2005).

Mutl (2009) derived a constrained likelihood estimator which is equivalent to using the spatial Cochrane-Orcutt transformation and then maximizing the QML function derived under the assumption that the disturbances are independent. Let Ω_ε denote the variance covariance matrix of $\varepsilon_{i,t}$ and Υ denote the variance covariance matrix of the initial observation in first differences. The matrix Σ is defined as:

$$\Sigma = \begin{pmatrix} \Upsilon & -\Omega_\varepsilon & & 0 \\ \Omega_\varepsilon & 2\Omega_\varepsilon & & \\ & & \ddots & -\Omega_\varepsilon \\ 0 & & -\Omega_\varepsilon & 2\Omega_\varepsilon \end{pmatrix} \tag{5.44}$$

the matrix R is defined as:

$$R = \begin{pmatrix} I_m & & & 0 \\ -A & I_m & & \\ & & \ddots & \\ 0 & & -A & I_m \end{pmatrix} \tag{5.45}$$

and the matrix S corresponds to:

$$S = (\Delta x_1', \ldots, \Delta x_T') \cdot (\Delta x_1', \ldots, \Delta x_T') \tag{5.46}$$

The constrained likelihood function to maximize with respect to $\tilde{\theta} = (vech\Upsilon', vech\Omega_\varepsilon', vecA')'$ is given by:

$$\begin{aligned} Q_N\left(\tilde{\theta}\right) = &-\frac{mNT}{2}\log(2\pi) - \frac{N}{2}\log|\Sigma| + \log\left|I_{mNT} - \hat{\lambda}W\right| \\ &-\frac{1}{2}tr\left[R'\left(I_{mNT} - \hat{\lambda}W\right)\left(I_N \otimes \Sigma^{-1}\right)\left(I_{mNT} - \hat{\lambda}W'\right)RS_N\right] \end{aligned} \tag{5.47}$$

taking the consistent estimator $\hat{\lambda}$ of λ as given. The Monte Carlo simulation results show that the constrained likelihood procedure works well in small samples. This estimator is chosen to analyze regional labor market dynamics after a region-specific labor demand shock.

5.2 Data and some stylized facts

This section provides information about the data and variables applied in this study. The definition of the regional variables entering the PVAR are described and stylized facts for these variables are presented. Further, descriptive analysis for the relationship of regional unemployment and labor mobility are provided. Finally, the construction of relative regional variables is described.

5.2.1 Data source and definitions

The data on employment, unemployment, population and labor mobility contains all people between the age of 15 and 64 years. This means the population corresponds to the working age population and migration is restricted to migration flows of the working age population.

Data on employment and unemployment measured in June of each year is provided by the German Federal Employment Agency. Data on employment includes all employees between 15 and 64 years covered by the social security system. Data on population is provided by the BBSR. The population is measured in December of each year. Data on wages and migration are provided by the German Federal Statistical Office. The available wages are the average annual wages per employee. The time series covers the period from 1999 to 2009.

The employment growth rate corresponds to changes in the number of employees working in a certain region. Employment measured by place of work is used here because the employment growth rate should reflect changes in labor demand.

The labor force is defined as the sum of employees measured at the place of residence and the unemployed. The participation rate is calculated as the ratio of the labor force to the working age population. The labor force employment rate is calculated as the ratio of employed persons measured at the place of residence and the labor force.

Migration is restricted to migration flows within Germany. Net-migration denotes the difference between the number of immigrants and emigrants in a certain region. The migration rate represents the relationship between net-migration and the working age population. Therefore, a negative regional net-migration rate indicates that losses in the working age population due to out-migration in a region are higher than gains in the working age population due to in-migration.

The net-commuting rate is calculated in a similar fashion to net-migration. Net-commuting corresponds to the difference between the number of in-commuters and the number of out-commuters. The net-commuting rate is the relation between net-commuting and the number of employees measured at the place of work. The out-commuting rate denotes the relation of out-commuters and the number of employees measured by place of residence. The in-commuting rate denotes the relation between in-commuters and the number of employees measured at the place of work.

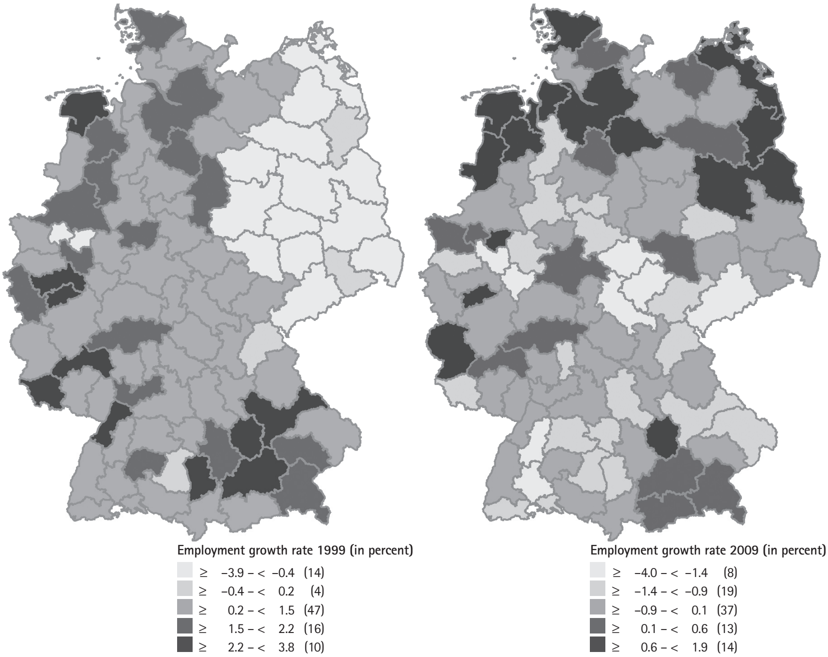
5.2.2 Stylized facts

In 1999, the German employment growth rate was almost one percent. Figure 5.1 shows that the German regions have experienced large differences in the employment growth rate. The regional planning units Munich and Ingolstadt reported employment growth rates above three percent whereas in Anhalt-Bitterfeld-Wittenberg and Lausitz-Spreewald, the number of employees decreased by more than three percent.

In 2009, the number of employees in Germany decreased by 0.3 percent. For the same year, large differences in regional employment growth are also observable. The highest employment growth rate in 2009 was reported in Ingolstadt with 1.9 percent.

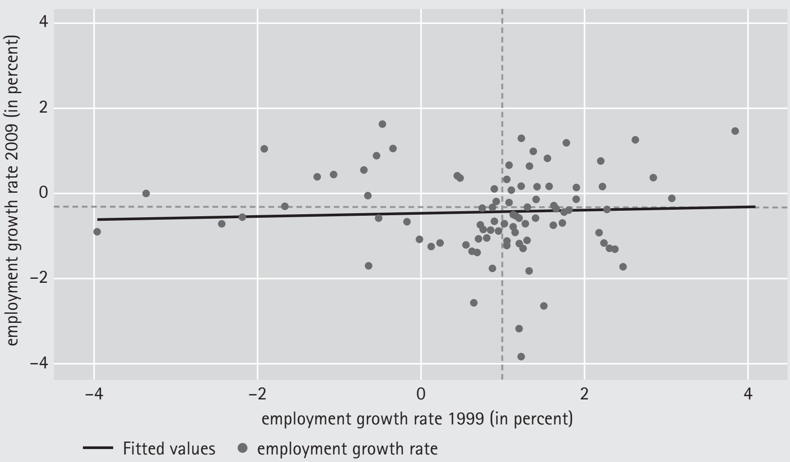
In contrast, the number of employees in Südthueringen and Schwarzwald-Baar-Heuberg decreased by more than three percent.

Figure 5.1: Employment growth for German regional planning units in 1999 and 2009



Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 5.2: Regional employment growth rates in Germany (1999 and 2009)



Notes: Slope of the regression line: 0.04 (t-stat.: 0.52, R^2 = 0.00), correlation coefficient: 0.05.
Source: Statistic of the German Federal Employment Agency, own calculations.

Comparing 1999 and 2009, differences in the ranking of the regional planning units according to their employment growth rates are observable.[7] 14 of the 17 regional planing units which reported a decrease in the number of employees in 1999, were located in East Germany. The three West German regional planning units were Emscher-Lippe, Dortmund and Oberfranken-Ost. In contrast, only five of the 17 regional planning units with the lowest employment growth rates in 2009 were located in East Germany. Further, only one of the 17 regions with the most unfavorable employment growth rates in 1999 remained in this group in 2009. Moreover, the regional planning units Berlin, Halle/Saale, Emscher-Lippe, Prignitz-Oberhavel, Uckermark-Barnim, Vorpommern and Dortmund lost employment in 1999 but reported a positive employment growth rate in 2009 (in contrast to the German average).

Figure 5.2 also shows that there has been a high degree of mobility between regional planning units with an above and a below average employment growth rate compared to the German rate in 1999 and 2009.[8] 14 regions with a below average employment growth rate in 1999, reported an above average regional employment growth rate in 2009. 30 regions with an above average regional employment growth rate in 1999, reported an below average growth rate in 2009. This means that compared to 1999, nearly 50 percent of the regional planning units changed their position in comparison to the German employment growth rate in 2009.

More results indicate that the ranking of the regions due to their employment growth rates is less persistent. The R^2 from the regression with regional employment growth rates in 2009 as the endogenous variable and the employment growth rate in 1999 as an exogenous variable is near zero (0.003). The slope of the regression line is 0.04, and the regression coefficient is not significantly different from zero. The correlation coefficient at 0.05 is very low.

In contrast to the employment growth rate, the labor force employment rate, the participation rate as well as the wages per employee show persistent behavior. The ranking of the regions according to these variables remained remarkably stable during the last ten years (see figure 5.4, figure 5.5, and figure 5.6).

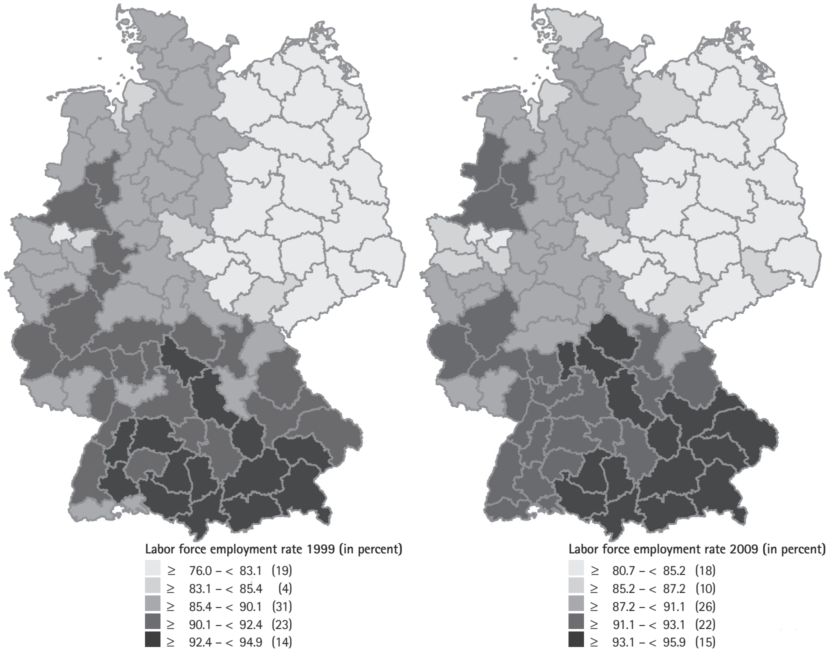
In 2009, the labor force employment rate in Germany varied between 80.8 percent in Mecklenburgische Seenplatte and 95.8 percent in Ingolstadt. In general, regional planning units with low labor force employment rates were located in East Germany, the North West of Germany and the Ruhr area. The regional

7 This section compares the ranking of the regions for two years only. Therefore, the observed pattern might only be representative for these two years. Note, that the relationship observable for 1999 and 2009 remains stable considering other years.

8 The dashed lines denote the German employment growth rates in 1999 and 2009.

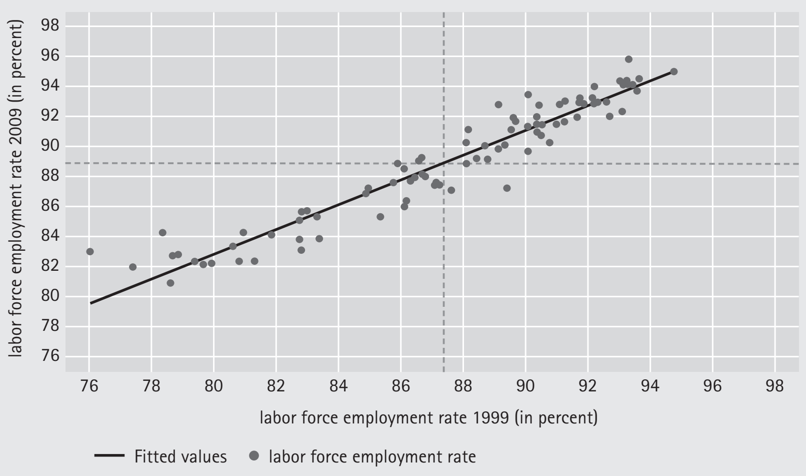
planning units with the highest labor force employment rates were located in the South of Germany (see figure 5.3).

Figure 5.3: Labor force employment rates for German regional planning units in 1999 and 2009



Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 5.4: Regional labor force employment rates in Germany (1999 and 2009)

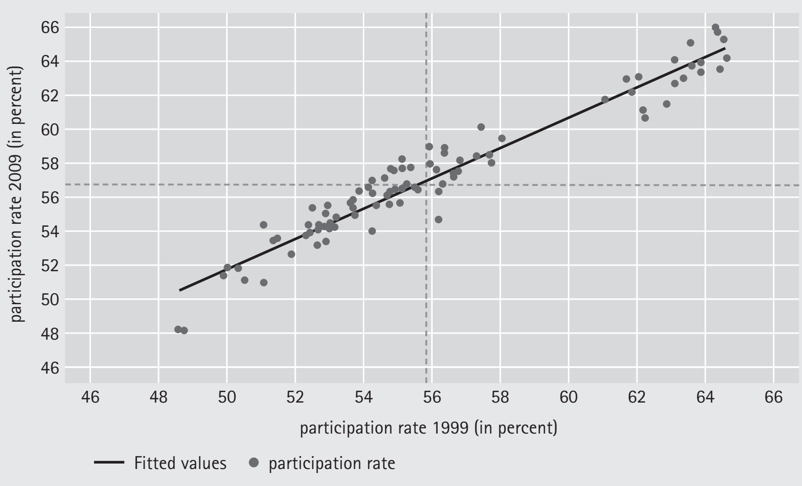


Notes: Slope of the regression: 0.82 (t-stat.: 32.20, R^2 = 0.92), correlation coefficient: 0.96.
Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 5.4 shows that the geographical distributions of regional labor force employment rates in Germany did not change very much during the last ten years. Compared to the regional employment growth rate, there was less fluctuation between the group of regions with an above and below average labor force employment rate. Only seven regional planning units changed between these groups. The correlation coefficient for regional labor force employment rates in 1999 and in 2009 amounts to 0.96. The regression line has a slope of 0.82 and the R^2 is 0.92. These results indicate that the ranking of the regional planning units according to their labor force employment rate was very stable.

Figure 5.5 reveals that the regional planning units are grouped into two different categories according to their participation rates. The group of regions with high participation rates consists of East German regional planning units. The reason for the high participation rates in East Germany compared to West Germany, is the notably higher female labor market participation in the East. Among the East German regional planning units, only Berlin realized a participation rate in 1999 and 2009 that was similar to the regional participation rates in West Germany.

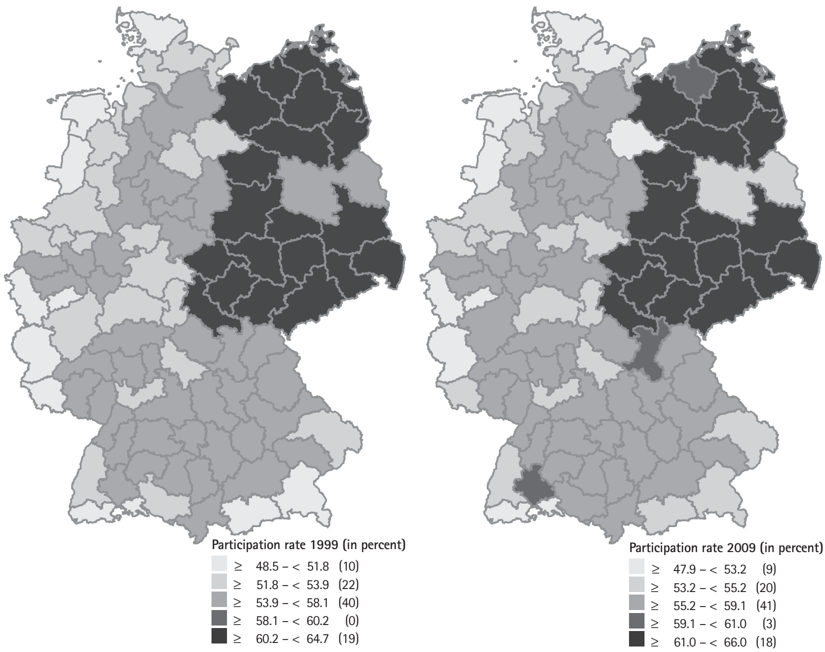
Figure 5.5: Regional participation rates in Germany (1999 and 2009)



Notes: Slope of the regression line: 0.89 (t-stat.: 36.02, R^2 = 0.94), correlation coefficient: 0.97.
Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

In 2009, Trier and Hochrhein-Bodensee reported participation rates below 50 percent, whereas the participation rates in East German regional planning units exceeded the value of 61 percent. The highest value was reported in Altmarkt with 65.9 percent. However, differences in regional participation rates between East and West Germany were more pronounced in 1999 compared to 2009 (see also figure 5.6). In 1999, Oberfranken-West realized the highest participation rates among the West German regional planning units with 58.1 percent. This was three percentage points below the participation rate of Uckermark-Barnim that reported the lowest participation rate among the East German regional planning units. In 2009, Schwarzwald-Baar-Heuberg was able to realize a participation rate similar to East German regions. In Schwarzwald-Baar-Heuberg, the participation rate in 2009 amounted to 60.0 percent and the participation rate of Mittleres Mecklenburg/Rostock was 60.6 percent. Apart from the differences between East and West Germany, no clear regional pattern is observable for regional participation rates (see figure 5.6).

Figure 5.6: Participation rates for German regional planning units in 1999 and 2009



Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

The correlation coefficient for regional participation rates in 1999 and 2009 amounts to 0.97. The slope of the regression line is 0.89 with an R^2 of 0.94. Only ten of the 91 regional planning units changed their position in comparison to the average German participation rate. Eight regional planning units with a below average participation rate in 1999, realized an above average participation rate in 2009. Two regions changed from the group of regions with an above average participation rate in 1999 to the group of regions with a below average participation rate in 2009. These findings show that the geographical distribution of participation rates within Germany was very stable during the last ten years.

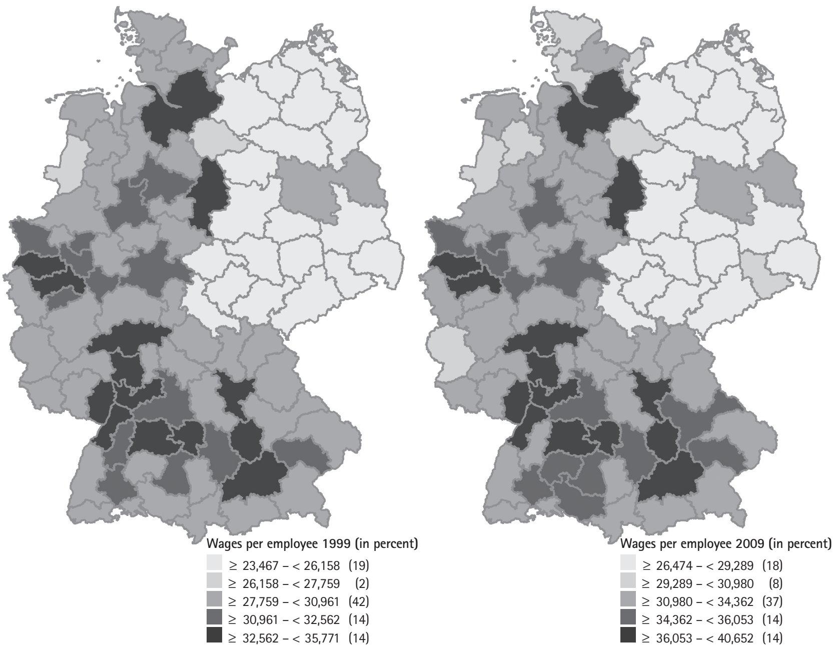
Figure 5.7: Regional wages per employee in Germany (1999 and 2009)

Notes: Slope of the regression line: 1.03 (*t*-stat.: 38.69, R^2 = 0.94), correlation coefficient: 0.97.
Source: Regional Accounts, own calculations.

Figure 5.7 shows that regional planning units are grouped into three different categories according to regional wages per employee. Large agglomerations in West Germany such as the regional planning units Hamburg, Duesseldorf, Cologne, Munich, Stuttgart and Rhein-Main exhibit by far the highest wages per employee in 1999 and 2009 (see also figure 5.8). Moreover, regional planning units with a strong specialization in car manufacturing (Braunschweig, Ingolstadt), and the regional planning units located in the Rhine-Neckar-Triangle (Starkenburg, Rheinpfalz, Unterer Neckar) belong to this group. The remaining regional planning units in this group are all located in Baden-Wuerttemberg. The other West German regional planning units as well as Berlin appear at the center of the picture. The East German regional planning units are situated further away from the national average in both periods.

Wages per employee show strong persistent behavior during the last decade. Only nine of the regional planning units changed their position in relation to the German average between 1999 and 2009. Moreover, the correlation coefficient for regional wages per employee in 1999 and 2009 is high with 0.97. In addition, the fitted regression line with a slope of 1.03 supports these findings.

Figure 5.8: Wages per employee for German regional planning units, 1999 and 2009



Source: Regional Accounts, own calculations.

These results for German regional employment growth, the regional labor force employment rate, the regional participation rate and regional wages are in line with other studies which consider European countries. The ranking of regions according to the labor force employment rate (the unemployment rate respectively), the participation rate, and wages, appeared to be very persistent over time. In contrast, regional employment growth rates were found to be characterized by low or modest persistence respectively. This result appears to be less surprising. Stocks such as the employment rate are usually considered as more persistent over time compared to flows such as the employment growth rate. However, it seems to be noteworthy that the findings for US states by Blanchard/Katz (1992) indicate very persistent regional employment growth rates and less persistent unemployment rates.

5.2.3 Labor mobility in Germany

The findings of the regional evolutions literature show that labor mobility is an important adjustment channel after a labor demand shock. However, labor mobility is usually limited to migration whereas little attention is paid to the role of commuting. This does not only hold for the regional evolutions literature.

Patacchini/Zenou (2007) and Elhorst (2003) point out that most studies about regional labor market disparities and regional labor mobility tend to focus on the impact of migration flows and neglect the role of commuting. For Germany, Granato et al. (2011) examine the relationship between regional labor market disparities and labor mobility considering migration and commuting. This section takes a closer look at both labor mobility measures.

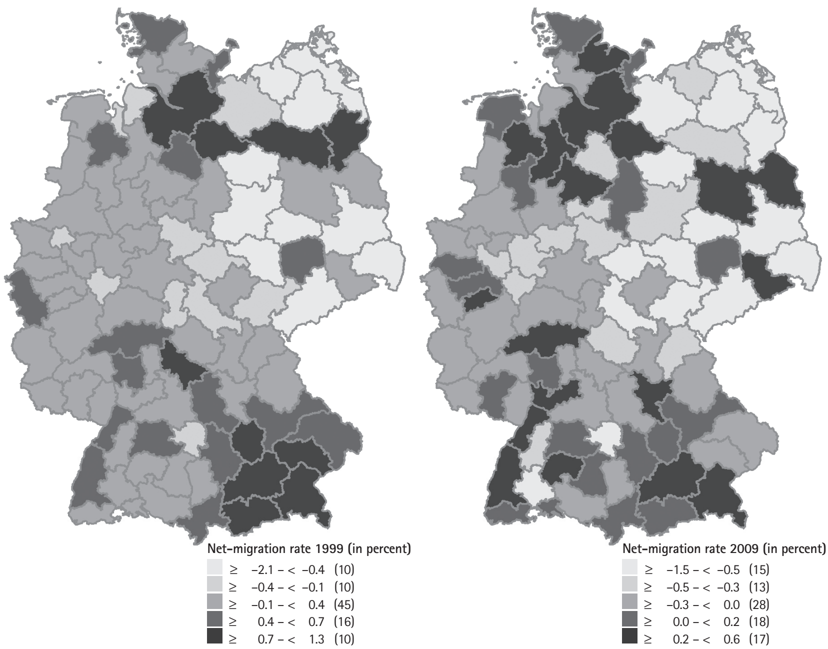
In 2009, the net-migration rate of German regional planning units varied between -1.4 percent in Altmark, and 0.5 percent in Rhein-Main. It is no surprise that a West German regional planing unit realized the highest net-migration rate and an East German regional planning unit realized the lowest net-migration rate. A common feature of internal migration in Germany since reunification is that people leave East Germany and move to West Germany. Wage differences, employment opportunities, differences in labor productivity and gradually shrinking subsidies for East German regions are identified as reasons for the migration decision (see, for example, Alecke/Untiedt 2000, Hunt 2000, Burda/Hunt 2001, Parikh/Leuvensteijn 2002, Burda 2008, and Alecke/Mitze/Untiedt 2010).

The working age population losses in East Germany due to internal migration appeared to be slightly more pronounced in 2009 than in 1999. In 1999, some regions in East Germany located around the regional planning unit of Berlin realized positive net-migration rates as well as Westmittelsachsen that includes the city of Leipzig. However, twenty years after reunification, Berlin and Oberes Elbtal/Osterzgebirge including the city of Dresden, were the only regional planning units in East Germany with a positive net-migration rate. In all other East German regions was the number of emigrants higher than the number of immigrants in 2009.

For West German regional planning units, no clear regional pattern is observable. Most of the agglomerations in West Germany such as Munich, Industrieregion Mittelfranken, Hamburg, Duesseldorf, Cologne or Rhein-Main, reported positive net-migration rates. For rural regional planning units in West Germany, both negative and positive net-migration rates are observable.

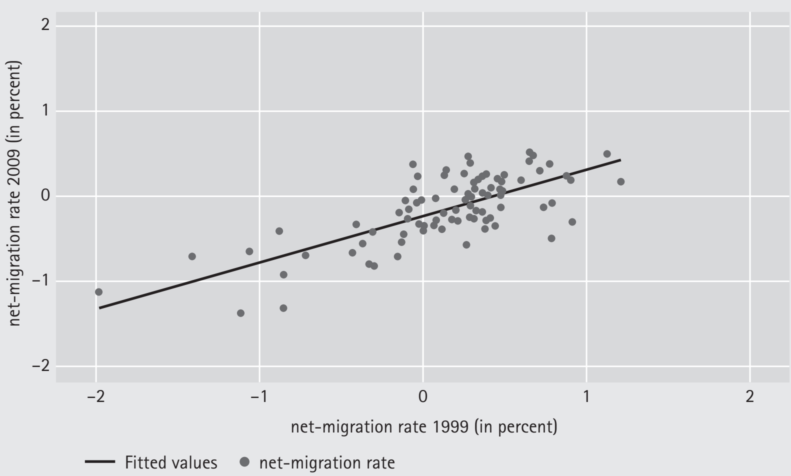
Figure 5.10 shows that the relationship between regions with population gains and regions with population losses due to internal migration was stable during the last ten years. There is a clear linear relationship between regional net-migration rates in 1999 and 2009. These results show that the regions of origin of internal migration and the target regions of internal migration in 1999 and 2009 were very similar.

Figure 5.9: Net-migration rates for German regional planning units, 1999 and 2009



Source: Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

Figure 5.10: Regional net-migration rates in Germany (1999 and 2009)

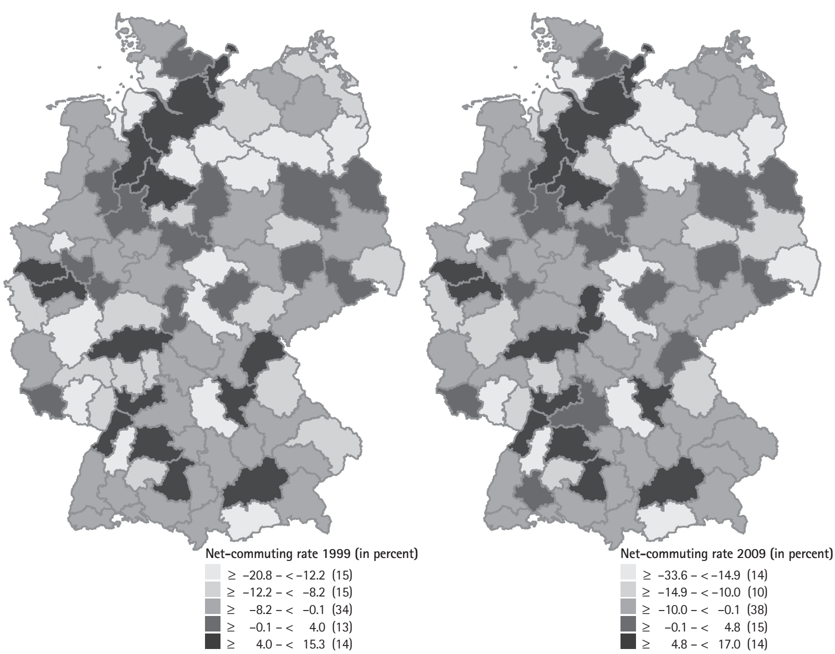


Notes: Slope of the regression line: 0.52 (*t*-stat.: 9.99, R^2 = 0.53), correlation coefficient: 0.72.
Source: Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

In 2009, the net-commuting rate varied between -33.5 percent in Uckermark-Barnim and 16.9 percent in Rhein-Main. All regional planning units with a net-commuting rate higher than 10.0 percent were located in West Germany (Unterer Neckar, Duesseldorf, Industrieregion Mittelfranken, Munich, Rhein-Main). The neighboring regions of these agglomeration centers exhibit negative values for the net-commuting rate. High negative values in East Germany are realized by the regional planning units surrounding the regional planning unit Berlin, while Berlin itself reported a net-commuting rate of 2.6. The highest net-commuting rate in East Germany with 3.1 percent was realized in the regional planning unit Oberes Elbtal/Osterzgebirge.

Commuting primarily takes place between agglomerations and rural regions. Nevertheless, differences between East and West Germany are still observable. Only 4 of the 20 East German regional planning units reported a positive net-commuting rate in 2009. Burda/Hunt (2001) already mentioned that especially workers in East Germany living in a region that shares a common border with West Germany tend to commute rather than to migrate. Einig/Pütz (2007) show the growing importance of out-commuting for less prosperous regional labor markets, especially for regions in East Germany.

Figure 5.11: Net-commuting rates for German regional planning units in 1999 and 2009

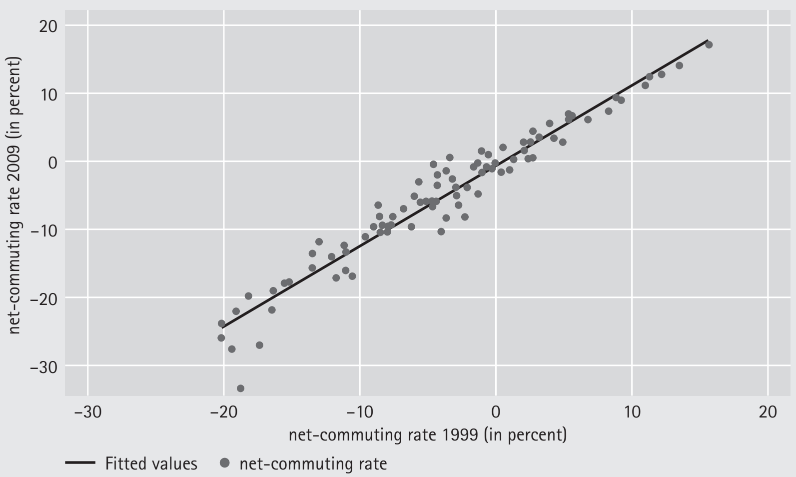


Source: Statistic of the German Federal Employment Agency, own calculations.

Comparing figure 5.12 and figure 5.10 shows that the ranking of the regions according to their net-commuting rates is much more persistent than in the case of regional net-migration rates. The regression line in figure 5.12 has a slope of 1.17, whereas the regression coefficient for the net-migration rate amounts to 0.52. The correlation coefficient for these two mobility measures also shows that the correlation is higher for net-commuting rates (0.97) than for net-migration rates (0.72).

Net-commuting rates provide only limited insights into the dynamics of commuting activities. If the number of out-commuters and the number of in-commuters change by the same amount, then net-commuting is not affected. Hence, stability of in-commuting and out-commuting is only one possible reason for a stable net-commuting rate. Whether there are changes in regional commuting activities or not can be seen by considering in-commuting rates and out-commuting rates separately. Figure 5.13 shows that there has been a rise in regional commuting activities during the last ten years. With 17.9 percent, the German (in) commuting rate was 3.3 percentage points higher in 2009 compared to 1999.[9] The four regional planning units with by far the highest out-commuting rates were Prignitz-Oberhavel, Uckermark-Barnim, Starkenburg and Emscher-Lippe. Only the first two regional planning units are located in East Germany. Emscher-Lippe is located in the Ruhr area and Starkenburg belongs to the Rhine-Neckar-Triangle.

Figure 5.12: Regional net-commuting rates in Germany (1999 and 2009)

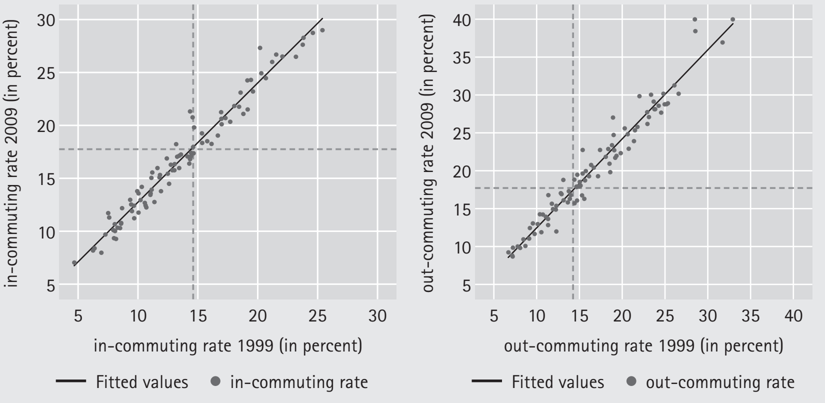


Notes: Slope of the regression line: 1.17 (*t*-stat.: 36.92, R^2 = 0.94), correlation coefficient: 0.97.
Source: Statistic of the German Federal Employment Agency, own calculations.

9 Here, the commuting flows between the German regional planning units are considered. Therefore, on the national level, the number of in- and out-commuters have to be identical by definition. Nevertheless, the German in- and out-commuting rate differs. The reason is the different denominators. The number of employees measured by place of work exceeds the number of employees measured by place of residence.

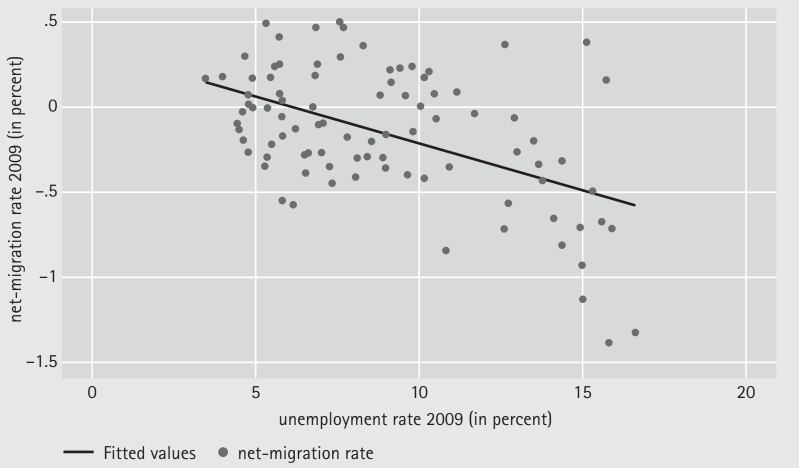
Figure 5.13 reveals that regional in-commuting rates as well as regional out-commuting rates show persistent behavior (see also figure A.6 and figure A.7 in the appendix). There were few changes of the regions of origin of the commuting workers and their target regions during the last ten years. The slope of the regression line for the in-commuting rate is 1.17 and 1.13 for the out-commuting rate. In both cases, the correlation coefficient is high and amounts to 0.97 for regional in-commuting rates and 0.98 for regional out-commuting rates.

Figure 5.13: Regional in-commuting and out-commuting in Germany (1999 and 2009)



Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 5.14: Regional net-migration rates and unemployment rates in Germany, 2009

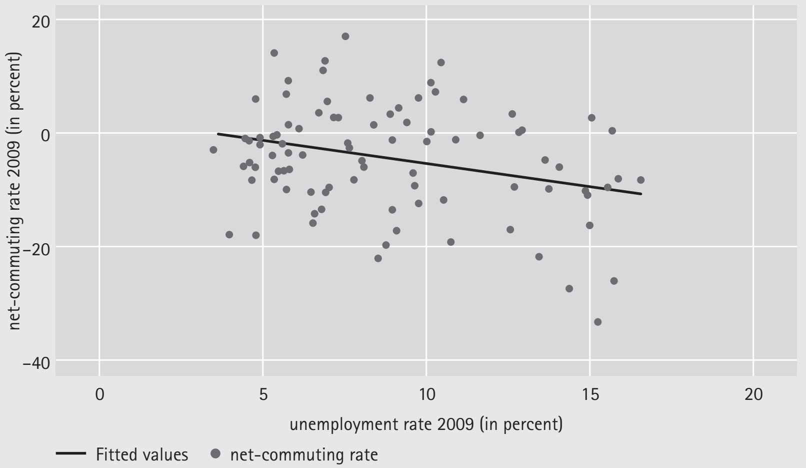


Notes: Slope of the regression line: –0.06 (*t*-stat.: –5.59, R^2 = 0.26), correlation coefficient: –0.50.
Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

Note, the descriptive analysis about commuting activities in Germany is based on regional planning units. This means that commuting activities between cities and their hinterland take place within these regional units. Hence, not all commuters are considered here, but instead the group of long-distance commuters. Nevertheless, commuting activities appear to be very pronounced in this group. Commuting seems a considerable form of labor mobility in the case of Germany.

To get a first impression of the relationship between regional labor market disparities and labor mobility, the regional unemployment rates and both mobility measures are investigated. Figure 5.14 reveals that there is a clear negative relationship between the net-migration rate and the unemployment rate. Regions with high unemployment rates realize negative net-migration rates. This means that regions with high unemployment are characterized by more emigrants than immigrants.

Figure 5.15: Regional net-commuting rates and unemployment rates in Germany, 2009



Notes: Slope of the regression line: −0.82 (t-stat.: −2.98, R^2 = 0.09), correlation coefficient: −0.30.
Source: Statistic of the German Federal Employment Agency, own calculations.

Figure 5.15 shows that there is also a negative relationship between the regional net-commuting rates and the regional unemployment rates. Workers tend to commute into regions with better employment opportunities. In contrast, Kunz (2012) finds a slight positive relationship between regional net-commuting rates and regional unemployment rates for districts. Cities usually realize positive net-commuting rates, whereas their rural neighboring regions realize negative net-commuting rates. However, unemployment rates for cities are usually higher compared to rural districts. This explains the positive relationship for German districts. In this chapter, the units of analysis are regional planning units. The main part of commuting activities between cities and their hinterland takes place within the regional planning units.[10]

The results by Granato et al. (2011) show that labor mobility seems to reduce regional disparities in unemployment in Germany. They also find that, compared to migration, commuting is less important for a reduction of labor market disparities in Germany. Figure 5.14 and figure 5.15 are in line with these findings.

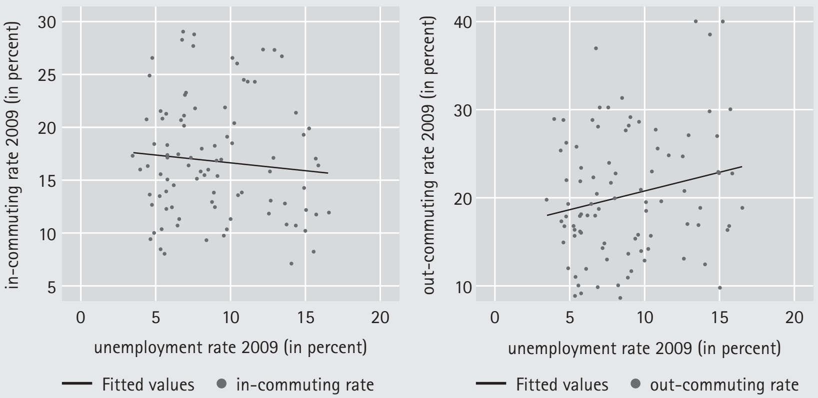
The regression results imply that there is a significant negative relationship between labor mobility and unemployment. However, the relationship between the regional unemployment rates and the measures for labor mobility appears to be more pronounced in the case of migration than in the case of commuting. Indeed, the regression coefficient amounts to -0.82 for the commuting case and only to -0.06 for the migration case but the R^2 is considerably higher in the migration case (0.26 compared to 0.09). Accordingly, the correlation coefficient for net-migration rates and unemployment rates with -0.50 is notably higher than for net-commuting rates and unemployment rates with -0.30.

Granato et al. (2011) also show that in- and outgoing mobility flows do not have to work symmetrically. To get a more detailed look at this issue, figure 5.16 presents the relationship for regional unemployment rates and regional in-commuting rates as well as regional out-commuting rates. If in-commuting and out-commuting flows were to work symmetrically, one would expect a negative relationship between in-commuting and unemployment, whereas the relationship between unemployment and out-commuting should be positive.

Figure 5.16 shows that the in- and out-commuting flows do not work symmetrically. The first panel of figure 5.16 provides no evidence that workers commute into regions with low unemployment rates. The slope of the regression line takes a negative value (-0.14) but is not significantly different from zero. The corresponding R^2 is near zero. In contrast, a slight positive relationship is observable for regional unemployment rates and regional out-commuting rates. The regression coefficient for the unemployment rate is 0.42 and significant at the five percent level. However, the corresponding R^2 with 0.04 is only small. Accordingly, the correlation coefficient is only small in 2009 for regional unemployment rates and in-commuting rates (-0.09) and for regional unemployment rates and out-commuting rates (0.21).

10 Note, that Kunz (2012) investigates the relationship between regional net-commuting rates and regional unemployment rates for the year 2004 whereas figure 5.15 presents results for 2009. However, the relationship between net-commuting rates and unemployment rates for regional planning units in 2004 is very similar to the one in figure 5.15.

Figure 5.16: Regional in-commuting, out-commuting and unemployment in Germany, 2009



Source: Statistic of the German Federal Employment Agency, own calculations.

These results show that there is a negative relationship between labor mobility and regional unemployment. Workers tend to out-commute from regions with fewer employment opportunities, whereas the target regions of commuting are not necessarily regional planning units with low unemployment rates. Further, the results show that job opportunities are by far not the only reason for the migration or commuting decision.

5.2.4 Measurement of relative regional variables

To derive the effects of a region-specific shock in labor demand, all variables have to enter the PVAR measured as relative regional variables. This is necessary to purge the regional variables from common movements. Following Decressin/Fatás (1995), Fredriksson (1999), Debelle/Vickery (1999), Choy/Maré/Mawson (2002), Pekkala/Kangasharju (2002a), Pekkala/Kangasharju (2002b), and Kunz (2012) we allow regional variables to differ in terms of their elasticity to movements of their national counterpart and construct relative regional variables measured as β-differences. Baddeley/Martin/Tyler (1998) show that β-differences can be considered as a combination of simple differences and simple ratios. Hence, the choice of β-differences is less restrictive compared to the assumption that the relationship between regional variables and their national counterpart are best described by either simple differences or simple ratios.

Let $\gamma_{i,t}^{n}$ denote the employment growth rate of region i at time t, and $\overline{\gamma}_{t}^{n}$ corresponds to the employment growth rate of (West) Germany at time t. The relative regional employment growth rate for region i measured as β-difference $\tilde{\gamma}_{i,t}^{n}$ is calculated in the following fashion:

$$\tilde{\gamma}_{i,t}^{n} = \gamma_{i,t}^{n} - \beta_{i}^{n}\overline{\gamma}_{t}^{n} \tag{5.48}$$

The coefficients β_i^n are unknown and have to be estimated. Here, the cyclical sensitivity approach by Thirlwall (1966) and Brechling (1967) is applied to determine $\hat{\beta}_i^n$ (see also section 2.2.1). A regression model of the form of equation (2.31) is estimated for each region separately with the regional employment growth rate as endogenous variable and the (West) German employment growth rate as exogenous variable. Then, the estimated coefficients $\hat{\beta}_i^n$ are applied to calculate the β-differences of the employment growth rate for each region as:

$$\tilde{\gamma}_{i,t}^{n} = \gamma_{i,t}^{n} - \hat{\beta}_{i}^{n}\overline{\gamma}_{t}^{n} \tag{5.49}$$

The β-differences for the logarithm of the labor force employment rate $le_{i,t}$, the logarithm of the labor force participation rate $pr_{i,t}$, the growth rate of net-commuting activity $\gamma_{i,t}^{ca}$, the growth rate of the number of in-commuters $\gamma_{i,t}^{ic}$, the growth rate of the number of out-commuters $\gamma_{i,t}^{oc}$ and the growth rate of wages per employee $\gamma_{i,t}^{wa}$ are calculated in a similar way following the cyclical sensitivity approach:

$$\tilde{le}_{i,t} = le_{i,t} - \hat{\beta}_{i}^{le}\overline{le}_{t} \tag{5.50}$$

$$\tilde{pr}_{i,t} = pr_{i,t} - \hat{\beta}_{i}^{pr}\overline{pr}_{t} \tag{5.51}$$

$$\tilde{\gamma}_{i,t}^{ca} = \gamma_{i,t}^{ca} - \hat{\beta}_{i}^{ca}\overline{\gamma}_{t}^{ca} \tag{5.52}$$

$$\tilde{\gamma}_{i,t}^{ic} = \gamma_{i,t}^{ic} - \hat{\beta}_{i}^{ic}\overline{\gamma}_{t}^{ic} \tag{5.53}$$

$$\tilde{\gamma}_{i,t}^{oc} = \gamma_{i,t}^{oc} - \hat{\beta}_{i}^{oc}\overline{\gamma}_{t}^{oc} \tag{5.54}$$

$$\tilde{\gamma}_{i,t}^{wa} = \gamma_{i,t}^{wa} - \hat{\beta}_{i}^{wa}\overline{\gamma}_{t}^{wa} \tag{5.55}$$

5.3 Results

This section presents the results for the dynamic response of the average region to a transitory one-period shock in region-specific employment growth. Note, that this study contributes to the existing literature in several ways. The original approach by Blanchard/Katz (1992) is augmented by allowing for different forms of labor mobility and it focuses on functional delimitated labor markets instead of administrative areas. Further, a new estimation procedure is applied to take the structure of the panel into account which is characterized by a large cross-sectional dimension and a small time dimension.

The section starts with a re-estimation of the three variable model in Kunz (2012) for West German districts using the PVAR estimator provided by Mutl (2009).[11] The aim of this analysis is to investigate whether the new estimation strategy matters, and if so, how. Then, the adjustment processes for West German regional planning units are examined.

Section 5.3.2 investigates the role of labor mobility during the adjustment process in more detail, distinguishing between commuting and migration for West German regional planning units. Section 5.3.3 analyzes the role of wages during the adjustment process. Finally, section 5.3.4 presents results for Germany as a whole.[12]

5.3.1 The classical approach revisited

To get an impression of how the new estimation method applied in this study affects the results, we start with a re-estimation of the model provided by Kunz (2012). Kunz (2012) applies the three variable approach by Blanchard/Katz (1992) for the 326 West German districts. The time series covers the period 1989 to 2004. A common lag length of two periods for each equation of the system was chosen. This specification is also applied for the other models examined in this chapter.

Figure 5.17 displays the dynamic response of the employment level, the unemployment rate and the participation rate induced by a one standard deviation shock in relative regional employment growth.[13] This labor demand shock leads to an immediate rise of the employment level by 1.44 percent. The unemployment rate decreases by 0.22 percent and the participation rate increases by 0.06 percent in the initial year of the shock. The responses of the three variables in the period of the shock are very similar to the results by Kunz (2012). According to his findings, a labor demand shock triggers an immediate increase of the regional employment level by 1.62 percent, a decrease of the unemployment rate by 0.21 percent and an increase of the participation rate by 0.05 percent.

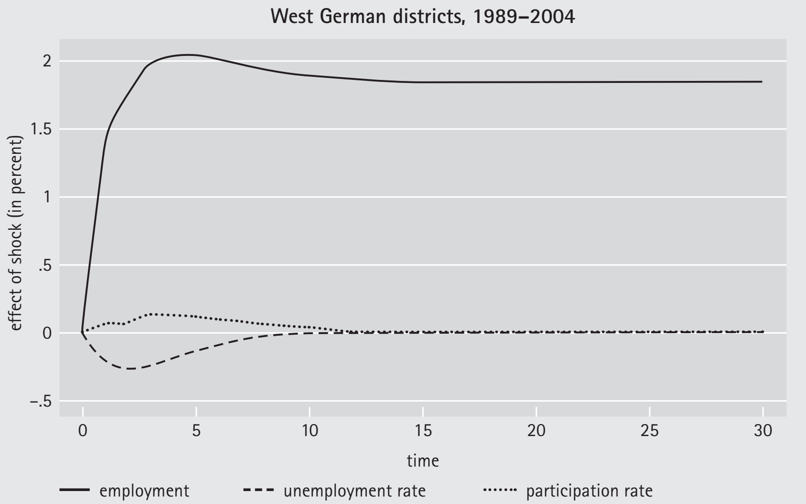
However, differences appear considering the adjustment path of the unemployment rate and the participation rate. According to Kunz (2012), the unemployment and participation rate reach their initial value already two years after the shock and it takes around six years until the effects of the labor demand shock dissipate.

11 MATLAB is used for the empirical analysis in this section.

12 Regression results for the different models are presented in the appendix.

13 For impulse response functions with estimated two-standard error bounds see figure A.8 to figure A.19 in the appendix.

Figure 5.17: Response of employment, unemployment and participation to a labor demand shock (West German districts, 1989 to 2004)



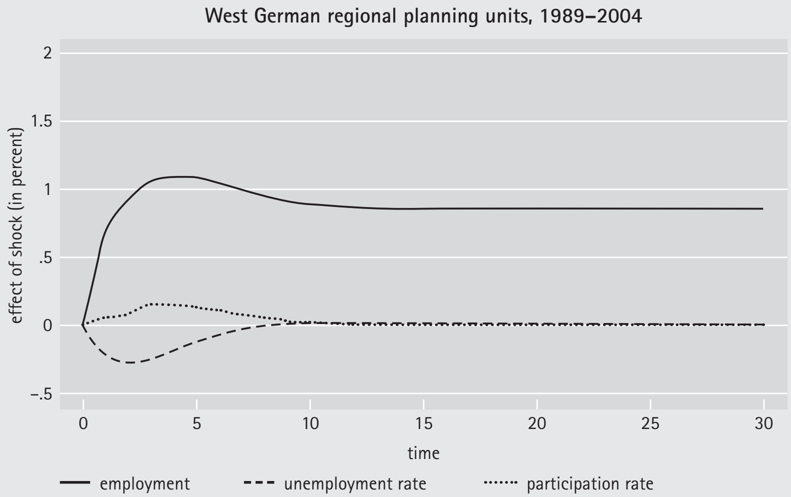
Source: Own calculations.

Here, the participation rate reaches its peak two periods after the shock and is 0.14 percent higher than before the shock. In the period after the shock, the unemployment rate reaches its lowest value. In this period, the unemployment rate falls short of its initial value by 0.26 percent. From then on, both variables start to return back to their initial values as they were before the shock occurred. However, it takes around twelve years until both measures return back to their initial values. These results indicate that the effect of the shock on the unemployment rate and the participation rate is more persistent compared to the findings in Kunz (2012). Moreover, the adjustment process of the two variables shown in figure 5.17 appears to be smoother compared to the findings by Kunz (2012).

The response of the employment level in figure 5.17 is in line with the findings from previous studies. The effect of a labor demand shock on the employment level becomes weaker over time, but the employment level remains above its initial value. Here, the employment level remains permanently 1.82 percent above its initial value. Because the unemployment and participation rate return back to their initial values after twelve years but the employment level remains permanently higher, labor mobility appears to be the main adjustment mechanism in the long run.

Comparing the findings by Kunz (2012) based on the LSDV estimator and the results presented here based on the PVAR estimator provided by Mutl (2009) shows some similarities but also some clear differences. The responses of the unemployment rate and the labor force participation rate in the initial period of the shock as well as the behavior of employment are very similar. Further, labor mobility seems to be the most important adjustment mechanism in the long run. However, the results for the adjustment paths of unemployment and participation show clear differences. The results presented here indicate that a region-specific labor demand shock has long-lasting effects on both variables and it takes more than a decade until these variables return back to their initial values. Therefore, the adjustment processes appear to be much more sluggish compared to the findings by Kunz (2012). These findings show that it is necessary to take the structure of the panel characterized by a large cross-sectional dimension and a small time dimension into account when examining the adjustment processes after a labor demand shock.

Figure 5.18: Response of employment, unemployment and participation to a labor demand shock (West German regional planning units, 1989 to 2004)



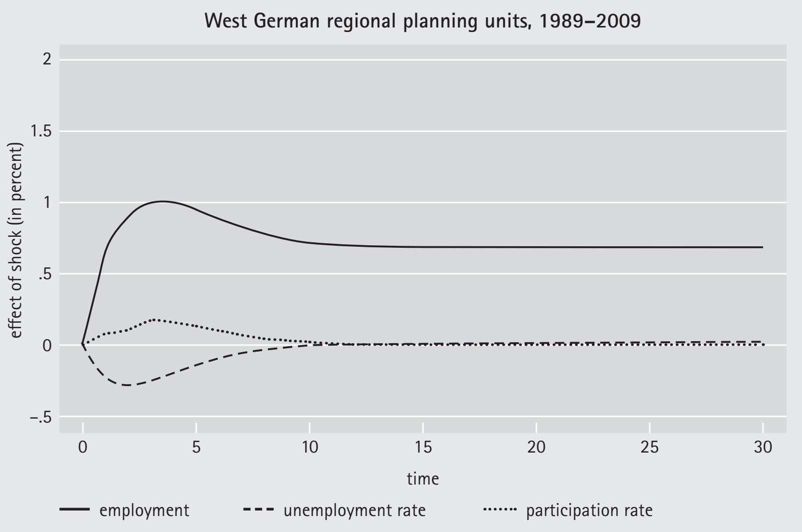
Source: Own calculations.

Next, the adjustment processes for the functional delimitated regional planning units are investigated. Figure 5.18 shows the adjustment process after a labor demand shock for the 71 West German regional planning units for the same time period. Fredriksson (1999), Choy/Maré/Mawson (2002), and Kunz (2012) emphasize that the adjustment dynamics after a regional labor demand shock and the size of the regional units under consideration are closely connected. Figure 5.18 shows that the response of the employment level according to a one standard deviation innovation in regional labor demand is considerably less pronounced for the larger regional planning units compared to the smaller districts. In the period of the shock, the employment level increases by 0.71 percent. This is in line with the findings by Kunz (2012). He showed that the response of the employment level for the smaller West German districts is more pronounced compared to the lager West

German federal states. In the long run, the employment level remains 0.85 percent above its initial value.

A region-specific labor demand shock triggers a fall of the unemployment rate by 0.23 percent and a rise of the participation rate of 0.05 percent. The short-run results for the West German regional planning units are similar to the results for the West German districts. In contrast, the adjustment process for the unemployment and participation rate is quicker in the case of the regional planning units. However, it still takes a decade until both variables return to their initial values.

Figure 5.19: Response of employment, unemployment and participation to a labor demand shock (West German regional planning units, 1989 to 2009)



Source: Own calculations.

Finally, the observation period is expanded up to the current period. Figure 5.19 shows the results for the 71 West German regional planning units but for a longer time period 1989 to 2009. The short-run results are very similar to the findings for the time period 1989 to 2004. Minor differences occur for the long-run behavior of the employment level, the unemployment rate and the participation rate. Hence, the adjustment processes appears to be stable over time.

In the initial year of the labor demand shock, the employment level increases by 0.70 percent and the unemployment rate decreases by 0.25 percent. The response of the participation rate with 0.08 percent is higher compared to the time period 1989 to 2004. In the long run, the employment level reaches a similar level as in the period of the shock and remains 0.68 percent above its initial value. However, the adjustment process for the unemployment and participation rate appears to be a little more sluggish once the years 2005 to 2009 are included in the data. It takes around twelve years until the unemployment and participation rate return back to their initial values.

All results provided in this section indicate that labor mobility is the major adjustment mechanism after a regional labor demand shock in the short as well as long run. This can be shown by decomposing the responses of the unemployment rate, the participation rate and labor mobility to a shock in labor demand using identity (5.17). In the case of West German districts, 15 percent of the shock in the initial year is absorbed by the unemployment rate and 4 percent by the participation rate. This means labor mobility accounts for 81 percent of the shock absorption in the initial year.

For the West German regional planning units and the time period 1989 to 2004, the unemployment rate accounts for 32 percent of the shock in the initial year and the participation rate accounts for 7 percent. Compared to the West German districts, labor mobility is less important as an adjustment mechanism. Nevertheless, more than 60 percent of the shock in the initial year is absorbed by labor mobility. This result is not surprising regarding the larger regional planning units. The main part of commuting activities between a city and the rural neighboring regions takes place within the regional planning units.

In addition, for West German regional planning units and the time period 1989 to 2009, labor mobility appears to be the most important adjustment mechanism. In the initial period of the shock, labor mobility absorbs more than 50 percent of the shock. However, compared to the results for the shorter time period, the role of the unemployment rate and especially the participation rate as adjustment channels were of growing importance including the recent years. The unemployment rate accounts for 36 percent of the shock and the participation rate for 11 percent in the initial year of the shock.

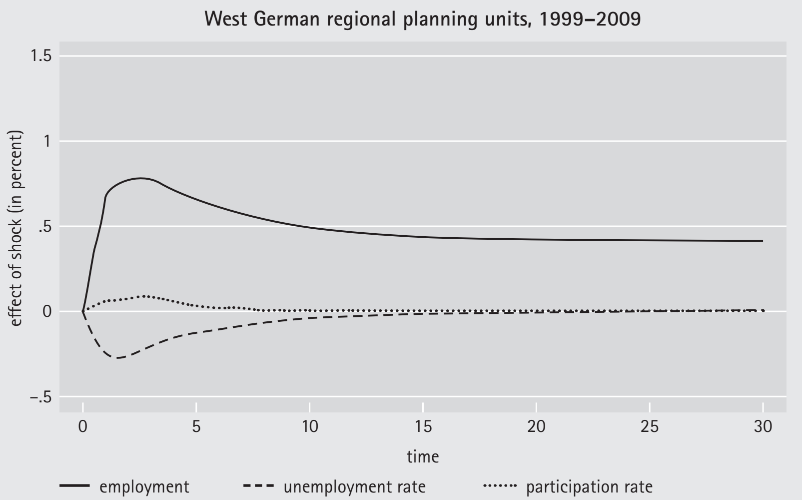
The results in this section provide information about the importance of labor mobility as an adjustment mechanism. However, in this three variable model based on Blanchard/Katz (1992) it is only possible to derive the response of labor mobility as a whole. The results provide no insights into the different forms of labor mobility. The next section takes a more detailed look on labor mobility as an adjustment mechanism.

5.3.2 The role of labor mobility for the adjustment process

The three variable model provided by Blanchard/Katz (1992) makes it possible to determine the impact of a regional labor demand shock on labor mobility. However, it is not possible to distinguish between migration and commuting as separate adjustment mechanisms after a shock. The aim of this section is to quantify the contribution of these two measures of labor mobility to the adjustment process.

Due to data restrictions, the time series covers the years from 1999 to 2009. To highlight differences in the adjustment process due to the shorter time period and differences due to the augmented set of variables entering the PVAR, the staring point here is again the three variable model. This model provides the baseline results.

Figure 5.20: Response of employment, unemployment and participation to a labor demand shock (West German regional planning units, 1999 to 2009)



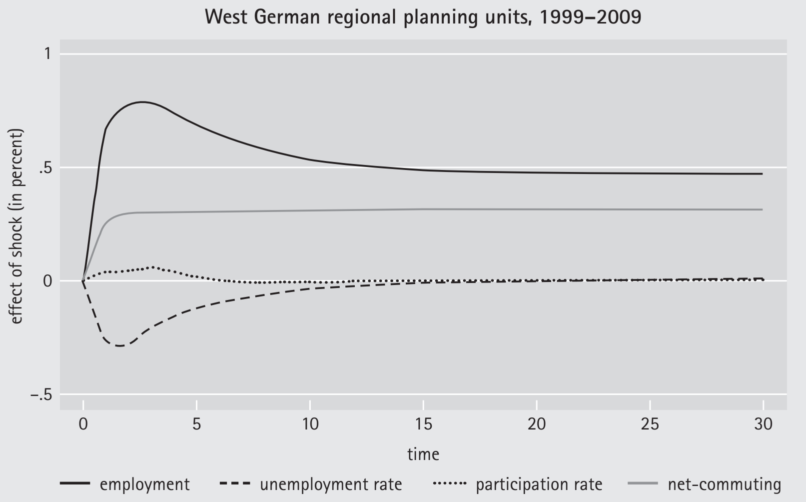
Source: Own calculations.

The results for the adjustment process for the time period 1999 to 2009 based on this model are provided in figure 5.20. The response of the employment level appears to be very similar to the findings for the period 1989 to 2009. A one standard deviation innovation in regional labor demand leads to a contemporaneous increase of the employment level by 0.68 percent. Two periods after the shock, the employment level is 0.78 percent above its initial value. From then on, the effect of the shock diminishes but the number of employees permanently remains on a higher level. In the long run, the employment level is 0.41 percent higher than its initial value.

The response of the unemployment rate in the initial period of the shock with 0.27 percent is also very similar to the time period 1989 to 2009. In contrast, the adjustment process of the unemployment rate appears to be more sluggish. Most of the effect of the shock is absorbed after fifteen years, but it takes up to 20 years until the effect of the shock completely disappears. With an increase of 0.05 percent, the response of the participation rate in the initial period of the shock is smaller compared to the time period 1989 to 2009. In addition, it only takes around six years until the effect of the shock on the participation rate disappears and the participation rate returns back to its initial value.

In the initial period of the shock, unemployment absorbs 40 percent of the shock and participation 7 percent. This means that in the year of the shock, over 50 percent of the shock is absorbed by labor mobility.

Figure 5.21: Response of employment, unemployment, participation and net-commuting to a labor demand shock (West German regional planning units, 1999 to 2009)



Source: Own calculations.

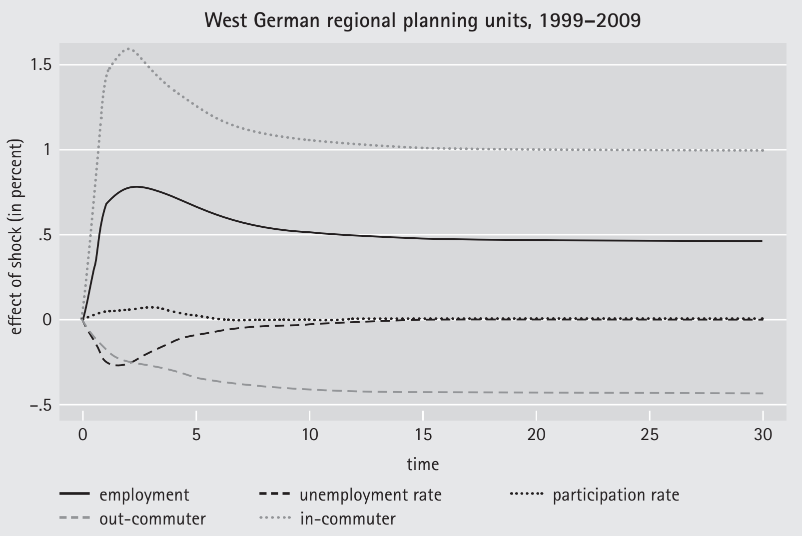
To distinguish between the impact of the shock on migration and commuting, the model is augmented by net-commuting activities represented by the ratio between employees measured by place of work and employees measured by place of residence. The vector of endogenous variables corresponds to equation (5.18). Based on the estimation results for the growth rate of net-commuting activity, the impact of the shock on the level of net-commuting activities is derived. The results for the model augmented by net-commuting activity are displayed in figure 5.21.

The findings indicate that a one standard deviation shock in labor demand triggers an immediate increase of net-commuting activities by 0.27 percent. Moreover, a labor demand shock has a permanent effect on net-commuting activities and in the long run, the ratio between employees measured by place of work and employees measured by place of residence is about 0.31 percent above its initial value. Compared to figure 5.20, the response of the unemployment rate in the initial period of the shock with 0.28 percent is now slightly higher, and the response of the participation rate with 0.04 percent slightly smaller.

According to these results, the unemployment rate absorbs 41 percent and the participation rate accounts for 6 percent of the shock in the initial period. This means that more than 50 percent of the shock is absorbed by labor mobility. However, migration appears to play only a minor role as an adjustment channel. Around 40 percent of the shock is absorbed by net-commuting activity, whereas changes in the working age population due to migration account for only 13 percent of the shock. Figure 5.21 also shows that even in the long run, commuting absorbs a larger part of the shock compared to migration.

Finally, the responses of gross-commuting flows are considered to examine whether a labor demand shock affects in-commuting and out-commuting symmetrically. The vector of endogenous variables of the PVAR corresponds to equation (5.20). Note, the impulse response functions reflect the development of the level of in-commuters and out-commuters. Analog to the case of employment, the estimated results of the in-commuter growth rate and the out-commuter growth rate are applied to compute the evolution of the level of in- and out-commuters.

Figure 5.22: Response of employment, unemployment, participation and gross-commuting to a labor demand shock (West German regional planning units, 1999 to 2009)



Source: Own calculations.

Figure 5.22 shows that in-commuters and out-commuters do not react symmetrically to an innovation in labor demand. In the year of the shock, the number of in-commuters increases by 1.46 percent, whereas the number of out-commuters decreases by 0.19 percent only. In the period after the shock, the number of in-commuters is 1.61 percent above its initial value. From then on, the number of in-commuters decreases but remains permanently around one percent above its initial value. A steady decrease of the number of out-commuters is observable for ten years. In the long run, the number of out-commuters is about 0.45 percent below the initial value.

The asymmetric response of out- and in-commuters gives a hint that the new job opportunities that go hand in hand with a positive regional labor demand are not distributed equally across employees. In this case, the decrease in the number of out-commuters should be higher than the increase in the number of in-commuters because travel costs decline for out-commuters if they can work in their region of residence. The higher increase in the number of in-commuters implies that new jobs require qualifications that not all people already living in the region are endowed with.

Another explanation for the asymmetric response might be that the new in-commuters and the out-commuters are characterized by an on average different degree of search intensity. If the new in-commuters were primarily unemployed before, it appears to be reasonable to assume that their search intensity to get a new job is higher compared to the group of out-commuters that are already employed. In this case, the smaller response of the out-commuters would reflect that people are less willing to give up their current job and change their employer solely for a new job in their region of residence.

However, these explanations only hold for a positive labor demand shock but not in the case of a negative labor demand shock. An underlying assumption of the model is that negative and positive shocks work symmetrically (see section 2.2.4). In the case of an unfavorable labor demand shock, the stronger response of the in-commuters might simply reflect that if in-commuters loose their jobs, they do not affect the number of unemployed in the region under consideration or the regional labor force because they do not live in this region. They can only affect these two measures in their region of residence. Hence, these results can also be interpreted in the sense that there are regional spill-over effects of the shock via labor mobility.

The response to a labor demand shock can also be expressed in the number of people instead of relative changes. This makes it more convenient to quantify the contribution of the different adjustment channels. However, Choy/Maré/Mawson (2002) point out that the impulse response analysis only provides the net impact of the labor demand shock on the variables in the model. Hence, a fall in the number of unemployed in the period of the shock only implies that the number of outflows from unemployment exceeds the inflows into unemployment but not that there are no inflows into unemployment from, for example, people out of the labor force or migrants. This has to be kept in mind when considering the results for the number of people.

Suppose the one standard deviation innovation in labor demand corresponds to 100 new jobs or 100 new employees measured by place of work respectively.[14] An increase of 100 employees measured by place of work goes hand in hand with 51.9 additional employees measured by place of residence. This implies that 48.1 of the new jobs are filled by commuters.[15] The number of in-commuters increases by 37.5 persons and 4.6 former out-commuters start working in their region of residence. The number of unemployed decreases by 38.5 people, and 28.0 migrants move into the region.

As the sum of migrants and former unemployed exceeds the number of additional employees measured by place of residence, this implies that the number of people out of the labor force has to increase by 5.7 persons. Of course, this is not a very intuitive result. One would expect that a positive labor demand shock goes hand in hand with a drop in the number of people out of the labor force. A reason for this finding might be the restrictive definition of the labor force. Here, the labor force includes the unemployed and the employees covered by the social security code. Hence, people out of the labor force also include self employed people as well as employees not covered by the social security code. Therefore, the people out of the labor force do not only consist of discouraged people. It seems appropriate to assume that an innovation in employment covered by the social security code also affects other forms of employment. Hence, an unemployed person getting a job that is not covered by the social security code leads to a decrease of the labor force. Similarly, if this person looses his or her job and becomes unemployed, the labor force increases.

Another explanation could be that only West Germany is considered here and that the western part of Germany is first and foremost the target region of internal migration in Germany (see section 5.2.3). Note, that the finding of a rise of people out of the labor force results from the very small response of the participation rate. This in turn means that the response of the labor force and the working age population has to be very similar. The pattern of internal migration in Germany is characterized by migration flows from East to West and this pattern was very stable during the last decades. Hence, these migration flows generally appear to be the result of unfavorable job opportunities in the East compared to the West, rather than region-specific shocks in West German regional planning units. However, the sample of cross-sectional units does not include the East German regional planning

14 These responses in the number of people for the average region are calculated based on the West German sample means of the labor force employment rate (E^{por} / LF = 0.89), the participation rate (LF / POP = 0.55), the in-commuting rate (0.18) and the out-commuting rate (0.16).

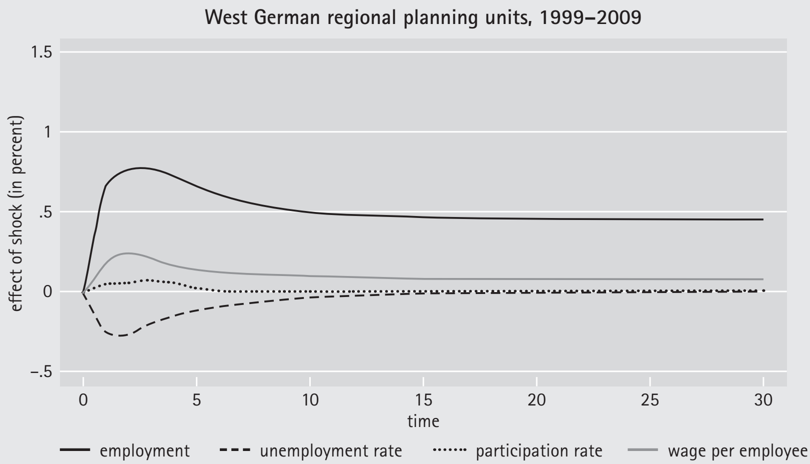
15 In-commuters do not affect the number of employees measured by place of residence because they do not live in the region. Out-commuters do not affect the number of employees measured by place of residence because they already live in the region.

units and this might lead to an overestimation of the migration response to a labor demand shock for West Germany.

5.3.3 The role of the wage feedback in the adjustment process

This section investigates the role of wages in the adjustment process. The starting point is the three variable model augmented by the growth rate of wages per employee. The vector of endogenous variables of the PVAR corresponds to equation (5.21), and all variables enter the PVAR measured as relative regional variables. For the impulse response analysis, the estimated results for the growth rate of wages per employees are applied to derive the development of the wage level per employees caused by a labor demand shock.

Figure 5.23: Response of employment, wages, unemployment and participation to a labor demand shock (West German regional planning units, 1999 to 2009)

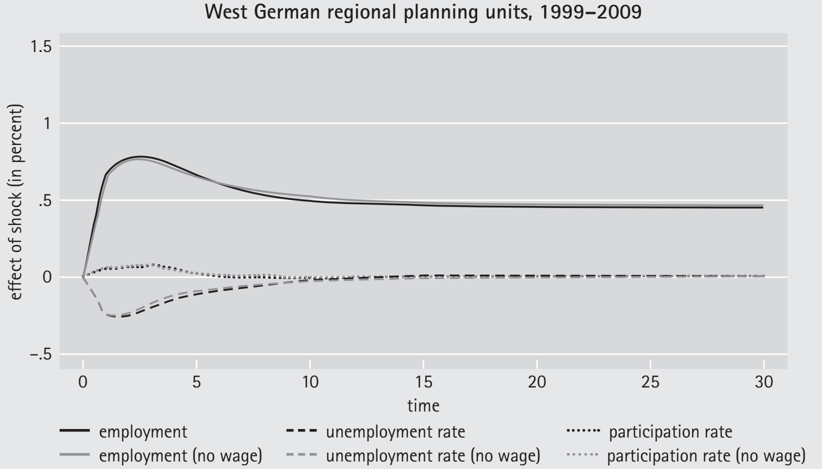


Source: Own calculations.

Figure 5.23 shows the responses of the employment level, the wage level, the unemployment rate and the participation rate to a one standard deviation shock in labor demand. In the initial period of the shock, the wage level increases by 0.20 percent. In the period after the shock, the wage level is 0.25 percent above its initial value. From then on, the effect of the shock on the wage level decreases, but the wage level remains permanently above its initial value. In the long run, the wage level is 0.08 percent higher compared to the time before the shock. The adjustment paths for the employment level, the unemployment rate and the participation rate are nearly identical to the results for the three variable model without wages presented in section 5.3.2.

To examine the effect of the wage feedback, we follow the approach suggested by Blanchard/Katz (1992) and recompute impulse response functions setting all the coefficients of lagged wages in the PVAR to zero. Responses of the employment level, the unemployment rate and the participation rate with and without wage feedback are presented in figure 5.24.

Figure 5.24: Response of employment, unemployment and participation with and without wage feedback (West German regional planning units, 1999 to 2009)

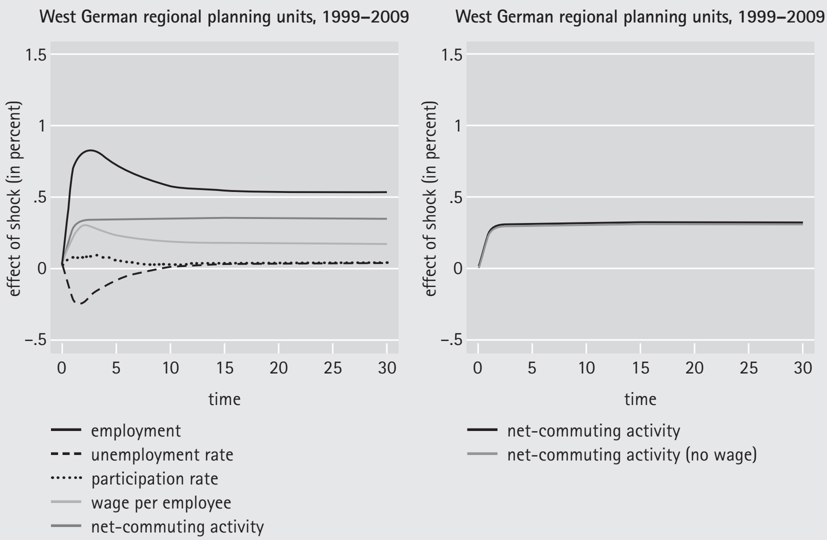


Source: Own calculations.

These results confirm the impression that there are only minor effects of the wage feedback on the adjustment process. It seems that in the short run, the increase of the wage level and the slightly more pronounced fall in the unemployment rate induces net in-migration and net in-commuting of labor. Hence, during the periods directly after the shock, the employment level allowing for the wage feedback is slightly higher compared to the case where the wage feedback is suppressed. However, in the long run, the higher wage level dampens the creation of new jobs and the response of the employment level but this effect is also very small. In the long run, the employment level remains about 0.46 percent above its initial level suppressing the wage feedback, and about 0.45 percent above its initial value in the model with wage feedback.

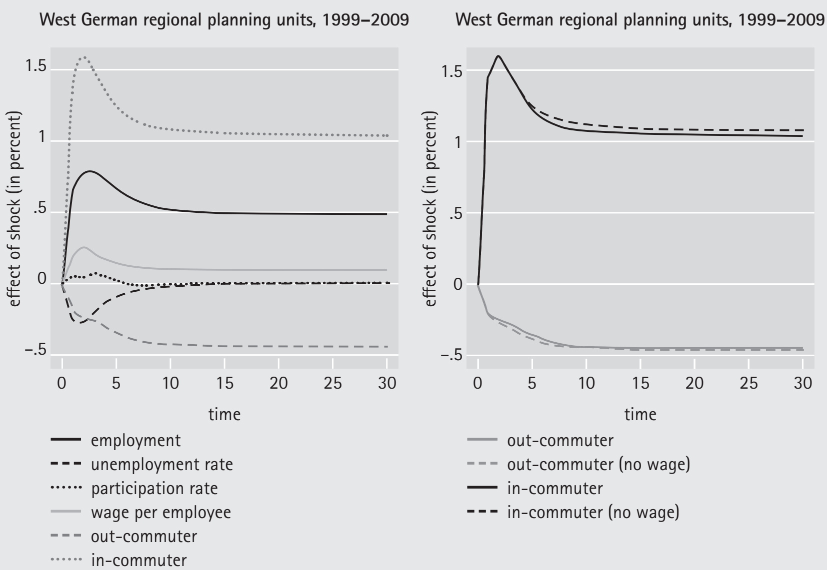
Allowing for a wage feedback, the response of the participation rate appears to be slightly more pronounced. However, in both cases, the participation rate returns back to its initial value six years after the shock. Further, the wage feedback appears to slightly accelerate the adjustment process of the unemployment rate. It takes 18 years until the unemployment rate returns to it initial value suppressing the wage feedback, but only 16 years allowing for a wage feedback.

Figure 5.25: Response of employment, wages, unemployment, participation and net-commuting to a labor demand shock (West German regional planning units, 1999 to 2009)



Source: Own calculations.

Figure 5.26: Response of employment, wages, unemployment, participation and gross-commuting to a labor demand shock (West German regional planning units, 1999 to 2009)



Source: Own calculations.

Figure 5.25 displays the results for the model including net-commuting activity. The vector of endogenous variables of the PVAR corresponds to equation (5.22). The left panel of figure 5.25 shows the responses of the employment level, the wage level, the unemployment rate, the participation rate and net-commuting activity, whereas the right panel displays the response of net-commuting activity with and without wage feedback. The adjustment path of net-commuting activity in both cases is nearly identical.

Finally, the model including gross-commuting flows is augmented by wages. The vector of endogenous variables of this PVAR corresponds to equation (5.23). The corresponding impulse response functions as well as the responses of the number of in- and out-commuters with and without wage feedback are displayed in figure 5.25.

As figure 5.26 shows, the wage feedback also has only minor effects on the number of in-commuters and out-commuters. Only in the long run does the wage feedback slightly dampen the response of the in-commuters. Without wage feedback, the number of in-commuters is about 1.08 percent higher compared to its initial value, whereas in the case with feedback, the number of in-commuters remains permanently 1.05 percent above its initial value. This is in line with the findings for the responses of the employment level.

The wage feedback does not appear to notably accelerate or dampen the adjustment process after a labor demand shock. Comparing the results of the models with and without wage feedback, shows that the responses of the model variables are almost identical. Only for the long run are very slight differences for the response of the employment level and the response of the number of in-commuters observable. These results are in line with the findings by Blanchard/Katz (1992), Debelle/Vickery (1999), Choy/Maré/Mawson (2002), and Leonardi (2004). The results of these studies indicate that the wage feedback does not alter the adjustment process much at all. For the West German regional planning units, this effect appears to be even smaller than in those studies.

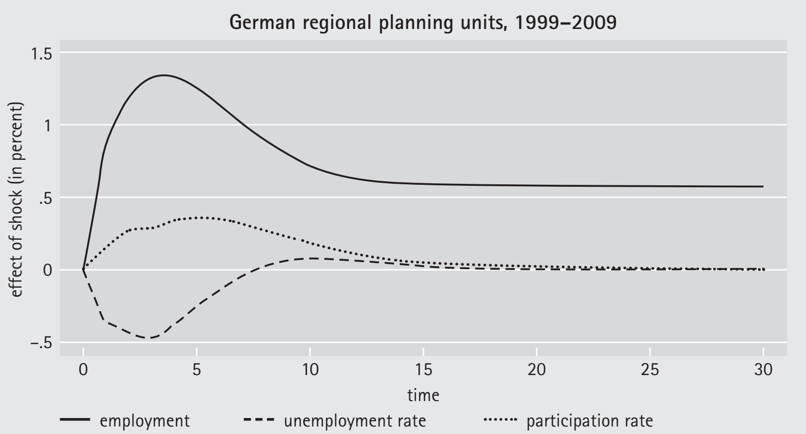
5.3.4 Region labor market dynamics in Germany

Everything we know about adjustment processes after a regional labor demand shock in Germany is confined to West Germany. Section 5.2.3 already showed that internal migration flows in Germany are characterized by gains in the working age population in West Germany and losses in East Germany both due to migration. It was argued in section 5.3.2, that this pattern leads to an overestimation of the role of migration in a model that only considers West German regions. A region-specific labor demand shock might not be strong enough to explicitly change this pattern.

The descriptive analysis in section 5.2.2 showed that regional labor market disparities between East an West Germany are still very pronounced. Clear differences in regional labor market conditions are observable for East West German regions. However, this heterogeneity does not imply that the two parts are not closely connected. Therefore, it appears to be reasonable to examine regional labor market dynamics after a region-specific labor demand shock for Germany as a whole.

The model includes region-specific fixed effects to account for unobserved regional heterogeneity. However, pooling these heterogeneous regions might lead to serious problems if the regional labor market disparities between East and West Germany are the result of different adjustment processes between the two parts of Germany. The PVAR assumes homogeneity of regression coefficients for the cross-sectional units pooled in the model. If the adjustment processes differ between East and West Germany, the findings of the impulse response analysis can only hardly be considered as the response of the "average" German region to a region-specific labor demand shock. Hence, the results have to be interpreted with caution. Nevertheless, considering all German regional planning units might provide some fruitful insights whether regional labor market dynamics after a region-specific labor demand shock differ between East and West Germany.[16] Hence, the different specifications of the PVAR of section 5.3.2 were re-estimated including all 91 German regional planning units.

Figure 5.27: Response of employment, unemployment and participation to a labor demand shock (German regional planning units, 1999 to 2009)



Source: Own calculations.

16 Note, it is not possible to estimate a PVAR for East Germany separately because of the small number of cross-sectional units. Further, a model for East Germany would also suffer from the problem that the pattern of mobility within Germany is characterized by flows from East to West Germany.

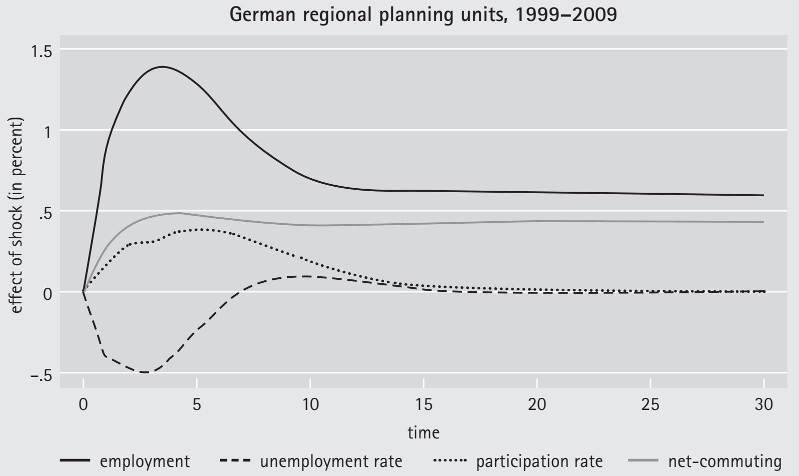
Figure 5.27 provides the response of the employment level, the unemployment rate and the participation rate after a labor demand shock for all German regional planning units for the period 1999 to 2009. Comparing figure 5.27 with figure 5.20 shows that the adjustment processes identified for all German regional planning units indeed differs from the findings from the West German model. Therefore, it does not seem appropriate to interpret the results as responses of the average German regional planning unit after an innovation in regional labor demand.

First, the response of the employment level is more pronounced. A one standard deviation innovation in labor demand leads to a contemporaneous increase of the employment level by 0.88 percent. Three years after the shock, the employment level is 1.34 percent above its initial value. From then on, the effect of the shock decreases, but in the long run, the employment level remains 0.57 percent above its initial value.

In the period of the shock, the unemployment rate decreases by 0.36 percent, the participation rate increases by 0.15 percent. It takes between six and seven years until the unemployment rate reaches its initial value again. However, it takes about 17 years until the effect of the shock on the unemployment rate cancels out. For the whole sample of German regional planning units, especially the adjustment process of the participation rate appears to be more sluggish. In the West German case it takes six years until the participation rate returns back to its initial value. Here, the participation rate reaches its highest value four years after the shock and it takes up to 25 years until the effect of the shock cancels out. This means that in the first year of the shock, 41 percent of the shock is absorbed by the unemployment rate, 17 percent by the participation rate, and labor mobility accounts for 43 percent of the shock.

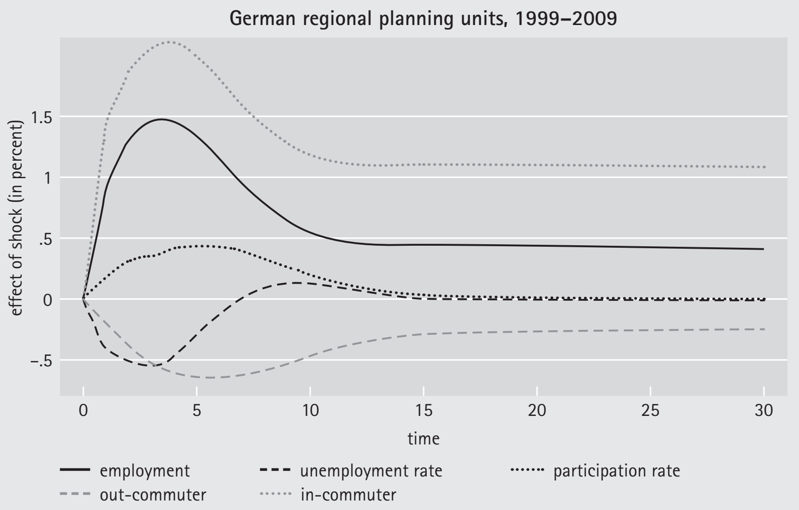
Figure 5.28 displays the response impulse functions for the model augmented by net-commuting activity. The responses of the employment level, the unemployment rate and the participation rate are very similar to figure 5.27. A one standard deviation shock in labor demand leads to a contemporaneous increase in net-commuting activity by 0.29 percent. In the long run, the relation between employees measured by place of work and employees measured by place of residence remains about 0.43 percent above its initial value. This means that in the initial period of the shock, the unemployment rate accounts for 44 percent of the shock, the participation rate accounts for 18 percent of the shock, and net-migration accounts for 32 percent. Hence, migration absorbs only 6 percent of the shock.

Figure 5.28: Response of employment, unemployment, participation and net-commuting to a labor demand shock (German regional planning units, 1999 to 2009)



Source: Own calculations.

Figure 5.29: Response of employment, unemployment, participation and gross-commuting to a labor demand shock (German regional planning units, 1999 to 2009)



Source: Own calculations.

The results for the model including gross-commuting flows are presented in figure 5.29. According to figure 5.29, a labor demand shock triggers an increase in the number of in-commuters by 1.45 percent and a decrease in the number of out-commuters by 0.20 percent. Two periods after the shock, the number of in-commuters is 2.12 percent above its initial value. From then on, the effect of the shock declines, and in the long run the number of in-commuters remains 1.10 percent above its initial value. In contrast to the West German case, the effect of the shock on the number of out-commuters starts to decline four periods after the shock. In the long run, the number of out-commuters remains 0.24 percent below its initial value.

Again, it is possible to express the effects of a labor demand shock in terms of the number of workers. If 100 new jobs are created in the course of a labor demand shock, 28.6 of these jobs are filled by commuters. There are 25.2 new in-commuters and 3.4 former out-commuters. Hence, an increase of 100 employees measured by place of work, goes hand in hand with an increase of 71.4 employees measured at their place of residence. 41.1 new workers were formerly unemployed, and 14.0 of the new workers came from outside the labor force. 16.3 new workers migrated from other regions.

In section 5.3.2, it was already argued that due to this pattern of internal migration flows in Germany, the response of migration was overestimated for West Germany. The findings for the model including all German regional planning units are in line with this point of view.

Compared to the findings for West Germany, especially the unemployment rate and the participation rate show a different behavior. However, also the results presented in this section indicate that the adjustment process is rather sluggish and a region-specific labor demand shock has long-lasting effects on these variables. Further, labor mobility and especially commuting appears to be the main adjustment mechanism in the long run.

The results presented in this section for Germany indicate that adjustment processes after a labor demand shock clearly differ between East and West Germany. Unfortunately, it is not possible to derive the response of the "average" East German regions from these results.

Labor market institutions are identical within Germany. Hence, this raises the question why adjustment processes differ between East and West Germany. An underlying assumption of this analysis is that the adjustment processes are symmetric in the case of positive and negative employment shocks. However, in 2009 the number of employees in East Germany is 10.6 percent below the value in 1999. In contrast, the number of employees in West Germany in 2009 is 2.4 percent higher compared to 1999. Therefore, there seems to be a higher probability for negative region-specific shocks in East Germany compared to West Germany and asymmetric adjustment processes could explain the differences.

Further, the results show that it might be problematic to examine the adjustment processes for regions characterized by heterogeneous labor market conditions as it is the case in East and West Germany. The results from the PVAR can only hardly be interpreted as the response of the "average" region. This should be kept in mind, especially if regional labor market dynamics are investigated for a group of regions located in different countries.

5.4 Conclusion

This chapter examined the adjustment processes of regional labor markets after a region-specific labor demand shock. Previous studies identified labor mobility as the main adjustment mechanism in the aftermath of a regional labor demand shock. The findings of this chapter also indicate that labor mobility is the most important adjustment mechanism for West German regional planning units even in the short run. In the initial year of the shock, labor mobility absorbs more than 50 percent of the shock.

However, labor mobility is usually confined to migration in the existing literature whereas commuting as an additional form of labor mobility is neglected. The aim of this chapter is to get a more detailed look on the role of labor mobility. The framework developed in this chapter allows us to distinguish between these two different forms of labor mobility. For the West German regional planning units, commuting was found to be more important than migration. In the initial period of the shock, commuting accounts for 40 percent of the shock, and migration accounts for 13 percent of the shock. Moreover, the results show that commuting activities are permanently affected by an innovation in regional labor demand and even in the long run a larger part of the shock is absorbed by commuting compared to migration. It appears to be noteworthy that the analysis is based on functional delimitated labor markets. Commuting activities between cities and their hinterland take place within the considered regional planning units. Nevertheless, commuting appears to be the main adjustment channel.

The results also show that in-commuting an out-commuting do not react symmetrically to a labor demand shock. If the labor demand shock goes hand in hand with the creation of 100 additional jobs, around 48 of the jobs are filled by in-commuters and around 5 jobs are filled by former out-commuters now working in their region of residence. This strong asymmetric response of the in-commuters and the out-commuters gives a hint that a labor demand shock does not affect all employees in the same way. The shock appears to be sensitive in terms of the labor market characteristics of people. However, another interpretation of this result might be that an unfavorable shock is exported via in-commuters into their regions of origin. More detailed analysis is needed to determine which employees are mainly affected by a labor demand shock.

Moreover, the findings show that an innovation in labor demand has long-lasting effects on the unemployment rates of West German regional planning units. It takes between 15 and 20 years until the effect of the shock completely disappears. These findings indicate that slow adjustment after a regional labor demand shock is a possible explanation for persistent disparities in regional unemployment.

In contrast, the response of the participation rate after a labor demand shock appears to be less pronounced for West German regional planning units. It takes around six years for the participation rate to recover.

The findings by Blanchard/Katz (1992), Debelle/Vickery (1999), Choy/Maré/Mawson (2002), and Leonardi (2004) already indicate that wages affect the adjustment process relatively little. According to this chapter, wages appear to play an even smaller role during the adjustment process for West German regional planning units.

So far, the existing regional evolutions literature dealing with Germany only considers West Germany. Pronounced labor market disparities between East and West Germany are still observable and the two parts of Germany are still heterogeneous in terms of regional labor market conditions. Hence, also the adjustment processes after a labor demand shock might differ between East and West Germany. The findings of the model including all German regional planning units are in line with this point of view. However, the results of this study provide no detailed insights into what are the differences in terms of the adjustment process between East and West Germany or to quantify these differences. Further, these findings have to interpreted with caution because it is not appropriate to interpret the results from the model pooling all German regional planning units as the response of the "average" German region.

Comparing East and West Germany shows that the labor market conditions are still heterogeneous. However, this does not mean that the two parts are not closely connected as the pattern of internal migration flows in Germany shows. A region-specific labor demand shock might not be strong enough to explicitly change this pattern characterized by flows from East to West Germany. Hence, the response of migration to a labor demand shock might be overestimated when only considering West Germany and not the whole country.

Further, the possibility of a negative labor demand shock appears to be higher for East German regional planning units compared to West German ones. Hence, another explanation for differences between East and West Germany might be asymmetric effects of negative and positive labor demand shocks. To test the underlying assumption of symmetric shocks made in this chapter could be an additional topic for further research.

Note, it remains somewhat of a black box what happens to migrants or commuters after leaving a region. For example, if an adverse labor demand shock triggers a fall in in-commuting and a rise in migration, it is not clear if these people find a job or if they are unemployed in their (new) home region. In the latter case, labor mobility might be a good adjustment mechanism if a region was hit by a shock. Otherwise, the effect of the shock would only be exported into another region. Hence, it might be another fruitful approach to examine the expansion of the shock in space. The spatial aspects of the estimator might serve as a corresponding tool for this analysis.

Chapter 6

6 What are the new insights into the evolution of regional labor market disparities?

This study examines the evolution of regional labor market disparities in Germany. It investigates the hypothesis of convergence for regional labor markets. In contrast to previous studies, the findings here suggest that region-specific labor market shocks are an important driving force of regional labor market disparities. This raises the question how long does it take until things return back to normal after a region-specific labor market shock. Following the framework provided by Blanchard/Katz (1992), this study additionally examines the adjustment processes after a region-specific labor demand shock.

The existing literature provides two broad threads of convergence analysis: the cross-sectional approach to convergence and the time series approach to convergence. The underlying assumption of the cross-sectional approach is that the regions under consideration are characterized by a transition process towards their steady states. Regional disparities simply reflect differences in the initial conditions. As soon as all regions reach their steady state, regional disparities should minimize or even disappear. Following this point of view, convergence can be considered as a catching-up process between favorable and unfavorable regions. In contrast, the time series approach to convergence emphasizes the role of region-specific shocks due to economic disturbances as the origin of regional disparities. Following this point of view, convergence can also be considered as an adjustment process after a region-specific shock. To get a comprehensive overview, this study follows both approaches to investigate the hypothesis of convergence of regional labor markets.

OECD (2005) already showed that regional unemployment disparities and regional employment disparities might behave differently. Although the large body of literature deals with convergence of regional unemployment disparities, it appears to be reasonable to consider both regional unemployment as well as regional employment. Hence, chapter 3 examines the hypothesis of convergence for unemployment rates of West German federal states and the time period 1968 to 2009 as well as for unemployment rates of all German federal states and the time period 1991 to 2009. Further, chapter 4 examines the hypothesis of convergence for employment rates of West German regional planing units and the time period 1989 to 2008.

The development of employment in Germany during the last years was characterized by a remarkable change of the skill composition. The number of low-skilled workers decreased, whereas the number of high-skilled workers increased. However, it is far from clear whether and how the change in the skill composition of employment affects the geographical distributions of employment prospects.

Therefore, the hypothesis of convergence is investigated for regional skill-specific employment rates as well as regional total employment rates. Skill-specific employment rates are calculated for high-skilled workers, medium-skilled workers and low-skilled workers. The results indicate that these employment subgroups behave in a different way than total employment. Hence, convergence analysis for total employment might only provide an incomplete picture about the evolution of regional employment disparities.

In the 1980s, the unemployment rates of West German federal states were characterized by a high degree of intra-distributional dynamics. In contrast, during the last twenty years, the ranking of (West) German federal states according to their unemployment rates was very stable. Similar results occur for the total employment rates of West German regional planning units during the time period 1989 to 2009. The same holds for high-skilled employment rates and low-skilled employment rates. In contrast, regional medium-skilled employment rates were characterized by a large degree of intra-distributional dynamics during the 1990s.

Evidence of β-convergence was found for unemployment rates of West German federal states. In contrast, the hypothesis of β-convergence has to be rejected when considering all German federal states. For regional total employment rates as well as for regional skill-specific employment rates, the findings indicate β-convergence. However, for regional employment rates, the speed of convergence appears to be rather slow.

The existence of β-convergence is a hint that there might be some form of catching-up process between favorable and unfavorable regions. However, a negative relationship between the initial values of a regional variable and their corresponding growth rates is only a necessary but not a sufficient condition for closing the gap between favorable and unfavorable regions and decreasing regional inequality. This means that the existence of β-convergence does not automatically imply σ-convergence.

Here the coefficient of variation is used as an inequality measure to investigate the hypothesis of σ-convergence. Neither for regional unemployment nor employment rates does the development of the coefficient of variation provides clear evidence of σ-convergence. For regional unemployment rates, the evolution of the coefficient of variation shows that periods of increasing inequality alternate with periods of decreasing inequality. Especially during the last twenty years, regional inequality seems to be mainly driven by cyclical movements and not by a continuous transition process.

While a favorable economic climate leads to a rise of regional unemployment disparities, regional inequality decreases during economic crisis. This means that during a boom, the unemployment rate decreases slower in regions with higher unemployment rates compared to those with lower unemployment rates. In contrast, during an economic downturn, unemployment increases slower in regions with high unemployment rates compared to those with low unemployment rates. Therefore, a positive economic climate is not sufficient to close the gap between low and high unemployment regions.

Similar results occurred for regional employment rates. However, the cyclical behavior of the dispersion of regional employment rates is less pronounced compared to regional unemployment rates. Further, with regard to regional high-skilled employment rates, a period of divergence was observable in the late 1990s.

The development of regional inequality in terms of (un)employment exhibits no clear trend but is mainly affected by the economic climate. Hence, simply comparing regional inequality at two points in time can easily lead to misleading results. Finding evidence of convergence and divergence first and foremost depends on where these two points are located within the business cycle. Moreover, because σ-convergence implies β-convergence, the concept of β-convergence also suffers from this problem. When investigating the hypothesis of σ-convergence it is possible to take this into account by examining the development of regional inequality over time. However, it appears to be rather questionable whether the concept of β-convergence can be considered as an appropriate approach to investigate the evolution of regional labor market disparities in Germany.

The results from the cross-sectional approach to convergence are contradictory to the point of view that regional unemployment rates and regional employment rates in (West) Germany are characterized by a transition process. Changes in the dispersion of regional unemployment and employment appear to be mainly driven by economic disturbances and shocks. Therefore, the time series approach to convergence appears to be more appropriate to investigate the evolution of regional labor market disparities in Germany than the classical cross-sectional approaches usually applied in the growth literature.

According to the definition of stochastic convergence given by Evans/Karras (1996), there is a stable long-run relationship between the regional variable and its cross-sectional average in the case of stochastic convergence. This implies that region-specific shocks should only have transitory effects on the deviations of regional variables from their national counterpart and they should return back to their initial value fairly quickly. Therefore, the deviations of regional variables from their national counterpart have to follow a stationary process. Computing the deviations of regional variables from their cross-sectional average leads to so called relative regional variables. The literature provides three different ways of calculating relative regional variables. They differ in the underlying assumption about the shape of the equilibrium relationship between regional variables and their national counterpart. To get an impression about the sensitivity of the results with regard to these assumptions, this study follows all three approaches to calculate relative regional unemployment rates. The hypothesis of stochastic convergence is examined for relative regional unemployment rate differences, relative regional unemployment ratios and relative regional unemployment rate β-differences.

The low power of univariate unit root tests is well known. Therefore, several studies use panel unit root tests to examine the hypothesis of stochastic convergence. The so called first generation panel unit root tests require the assumption of independent cross-sectional units. If this assumption is not valid, the first generation panel unit root tests tend to reject the null hypothesis of a unit root too often. The tests for cross-sectional independence by Pesaran (2007b) and Ng (2006) applied in this study show that relative regional unemployment rates in Germany exhibit cross-sectional dependence. Hence, so called second generation panel unit root tests relaxing the assumption of cross-sectional independency are necessary to investigate the hypothesis of stochastic convergence for German regional unemployment rates.

Here the PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common Components) approach provided by Bai/Ng (2004) is used to test the hypothesis of stochastic convergence. The basic idea of the PANIC approach is to first decompose the underlying time series into common factors which capture cross-sectional correlation and an idiosyncratic term. Then, each of these components are tested for a unit root.

Evidence of stochastic convergence of regional unemployment rates in (West) Germany following the PANIC approach is rather mixed. The results indicate stochastic convergence in the case of German regional unemployment differentials and β-differentials, and West German regional unemployment ratios. In all other cases the hypothesis of stochastic convergence has to be rejected. This shows that the findings might be sensitive according to the underlying assumption about the equilibrium relationship between the regional unemployment rates and their national counterpart. Further, the results are in contrast to the findings for West German regional unemployment by Möller (1995), Bayer/Jüßen (2007), and Kunz (2012) using first generation panel unit root tests but also to the findings of the first generation panel unit root tests applied in this study. Hence, the findings indicate that the existence of cross-sectional dependence is of key importance for the choice of an appropriate test procedure to investigate the hypothesis of stochastic convergence.

According to these results, region-specific shocks have long-lasting effects on German relative regional unemployment rate ratios as well as West German relative regional unemployment rate differentials and β-differentials. There are two different ways to think about such region-specific shocks (see, for example, Choy/Maré/Mawson 2002). A region-specific shock is one that either specifically occurs in a particular region or that affects more than one region but each region experiences a disproportionate impact of that shock.

In the case of stochastic convergence of regional unemployment rates, the idiosyncratic components as well as the common factors of relative regional unemployment rates have to follow a stationary process. In general, the rejection of the hypothesis of stochastic convergence is the result of a unit root in the common factor, whereas for the idiosyncratic components, the null hypothesis of a unit root is usually rejected. Further, the existence of common factors in relative regional unemployment rates indicates that regional unemployment rates are characterized by common components affecting the regions differently. Otherwise, the common components would have been eliminated by the construction of relative regional unemployment rates. This means that divergence of regional unemployment in Germany mainly occurs because of movements in regional unemployment rates that are common to all federal states but affect each federal state differently. In contrast, region-specific shocks that exclusively appear in a particular federal state seem to have only transitory effects.

Note, in this framework, cross-sectional dependence occurs via common factors shared by all regions. Hence, the assumption of cross-sectional independence of relative regional variables is not only important in terms of the choice of an appropriate panel unit root test, but additionally has a meaning in regards of content. The assumption of cross-sectional independence for relative regional variables implies that the regional variable is not characterized by common movements affecting each region in a different way. Hence, these forms of region-specific shocks as a source of divergence are excluded when assuming cross-sectional independence. This in turn implies that the assumption of cross-sectional dependence only holds if all common factors in the data are eliminated by the calculation of relative regional variables. This is only the case if the data contains only one common factor that is loaded with the same weight in each time series of the panel.

The definition of stochastic convergence holds if the common components of a regional variable as well as the remaining idiosyncratic component of a regional variable follows a stationary process. Moreover, the discussion in Banerjee/ Wagner (2009) shows that in the case of a stationary idiosyncratic component, the definition of stochastic convergence is in line with the existence of one common factor with homogeneous factor loadings even if this common factor is $I(1)$. Hence, it is also possible to examine the hypothesis of stochastic convergence for a regional variable by investing whether these restrictions imposed by the definition of stochastic convergence are valid. This study shows that the PANIC approach by Bai/Ng (2004) can be applied on the original time series to examine whether these restrictions hold. This alternative approach provides several advantages compared to the traditional approach of examining the hypothesis of stochastic convergence by testing relative regional variables for a unit root. For example, the results for regional unemployment rates indicate that making assumptions about the equilibrium relationship between regional variables and their national counterpart to construct relative regional variable is not trivial. Further, tests for cross-sectional dependence are required for the choice of an appropriate panel unit root test. Using the alternative approach, this is no longer necessary. Moreover, if the hypothesis of stochastic convergence has to be rejected, the alternative approach provides more detailed insights into the possible sources of divergence.

This study applies the alternative approach to investigate the hypothesis of stochastic convergence for regional employment rates. The results for the total employment rate provide evidence of the existence of stochastic convergence. In this case, the common factor as well as the remaining idiosyncratic components follow a stationary process. Hence, differences in regional total employment rates seem to be the result of different steady state values rather than weak and sluggish adjustment processes after a region-specific shock.

However, when examining regional skill-specific employment rates, evidence of stochastic convergence was only found for the high-skilled employment rate. The hypothesis of stochastic convergence was rejected for regional low-skilled employment rates and regional medium-skilled employment rates.

In the case of the low-skilled employment rate, divergence occurs because the idiosyncratic components contain a unit root. This means that a region-specific shock that falls specifically in one region has long-lasting effects on regional low-skilled employment. Therefore, such a shock might lead to a permanent deviation from the common trend. Decressin/Fatás (1995), Kunz (2012), and also this study identify labor mobility as the main adjustment mechanism after a region-specific labor market shock in Germany. Compared to the high-skilled employees, the low-skilled are less mobile. This could be one explanation for the long-lasting effects of a shock in the case of low-skilled employment and for temporary effects in the case of high-skilled employment.

With regard to the regional medium-skilled employment rates, the hypothesis of stochastic convergence has to be rejected because the PANIC approach identifies two common factors that are both $I(1)$. Further, one of these common factors is characterized by heterogeneous factor loadings. This is not in line with the definition of stochastic convergence. According to Autor/Levy/Murnane (2003) and Goos/Manning (2007) the skill-biased technological change is characterized by diminishing relevance of routine tasks, while the relevance of non-routine tasks becomes more important than a change in the formal qualification level of the employees. Hence, skill-biased technological change could also take place within skill-specific employment groups. The medium-skilled employees do not only represent by far the largest group among the employees, but they are also very heterogenous in terms of the tasks they perform. This might explain the results for medium-skilled employment rates.

The results indicate that regional total employment rates do not show stochastic convergence because the skill-specific employment subgroups show convergent behavior. The changes in the skill competition do not seem to affect the geographical distribution of employment prospects for total employment. However, it seems to go hand in hand with a redistribution of skill-specific employment prospects across regions.

Moreover, the findings show that a more detailed look on employment subgroups is necessary to get a complete picture about the evolution of regional labor market disparities. Employment subgroups can behave differently to total employment. Further, they appear to be an important driving force for the differences between regions. However, until now, only little is known about the role of and the interactions between different (un)employment subgroups in terms of the evolution of regional labor market disparities. Apart from this study, only Südekum (2008) provides empirical results about the relationship of employment subgroups and the evolution of regional labor market disparities. To the best of my knowledge, no study exists which investigates this relationship for unemployment subgroups. The analysis of (un)employment subgroups might be a fruitful topic for further research about the evolution of regional labor market disparities.

In contrast to previous studies, the findings in this study suggest that region-specific labor market shocks are an important driving force of regional labor market disparities. To examine the adjustment processes after a region-specific labor demand shock in detail, the framework provided by Blanchard/Katz (1992) is adopted and augmented. According to Blanchard/Katz (1992), the main adjustment channels after a region-specific shock are unemployment, labor force participation and labor mobility. However, in the regional evolutions literature, labor mobility is usually confined to migration whereas commuting as an additional form of labor mobility is neglected. This study provides a more detailed look on the role of labor mobility. The framework developed here makes it possible to distinguish between migration and commuting.

To examine the response of the representative region after a region-specific labor demand shock and the interactions between the different labor market measures, Blanchard/Katz (1992) suggest using a panel vector autoregressive (PVAR) model.

In general, a least square dummy variable (LSDV) estimator is applied on the PVAR. However, each equation of the PVAR represents a dynamic panel model. It is well known that results from a LSDV estimator are subject to the Nickell bias if the time dimension of the panel is not sufficiently large. Note, the majority of the existing studies adopting the framework by Blanchard/Katz (1992) do not take this into account. The panel in this study is characterized by a small time dimension and a large cross-sectional dimension. Therefore, the PVAR estimator for a panel with a small time dimension and large cross-sectional dimension additionally allowing for spatial correlation in the error term introduced by Mutl (2009) is applied here. The findings in this study suggest that it is of importance to take the structure of the panel into account when estimating the PVAR.

Several studies point out that the size of the regions under consideration might additionally affect the results. For example, even considering the same country it is reasonable to assume that the role of labor mobility as an adjustment mechanism is more pronounced for small regional units compared to large regional units. Therefore, the delimitation of the regional units is not trivial when investigating regional adjustment processes. Functional labor markets usually extend across administrative borders. To take this into account, German regional planning units are the units of analysis here.

Previous studies identified labor mobility as the main adjustment mechanism in the aftermath of a regional labor demand shock. The findings of this study also indicate that labor mobility is the most important adjustment mechanism for West German regional planning units even in the short run. In the initial year of the shock, labor mobility absorbs more than 50 percent of the shock. However, for the West German regional planning units, commuting was found to be more important than migration. In the initial period of the shock, commuting accounts for 40 percent of the shock and migration accounts for 13 percent of the shock. Moreover, the results show that commuting activities are permanently affected by an innovation in regional labor demand and even in the long run a larger part of the shock is absorbed by commuting compared to migration. Note, the main part of commuting activities takes place between cities and their hinterland and, therefore, within regional planning units. Nevertheless, commuting appears to be the main adjustment channel. Further, the findings show that in-commuters and out-commuters do not react symmetrically to a shock. The response of the in-commuters is much more pronounced. This is a hint that shocks might be sensitive in terms of labor market characteristics of workers and that a region-specific labor demand shock might be exported to other regions via commuters.

Moreover, the findings show that an innovation in labor demand has long-lasting effects on the unemployment rates of West German regional planning units.

It takes between 15 and 20 years until the effect of the shock completely disappears. These findings indicate that slow adjustment after a regional labor demand shock is a possible explanation for persistent disparities in regional unemployment. In contrast, the response of the participation rate after a labor demand shock appears to be less pronounced for West German regional planning units. It still takes around six years for the participation rate to recover.

According to this study, the role of wages during the adjustment process for West German regional planning units is only minor. This result is in line with the findings by Blanchard/Katz (1992), Debelle/Vickery (1999), Choy/Maré/Mawson (2002), and Leonardi (2004).

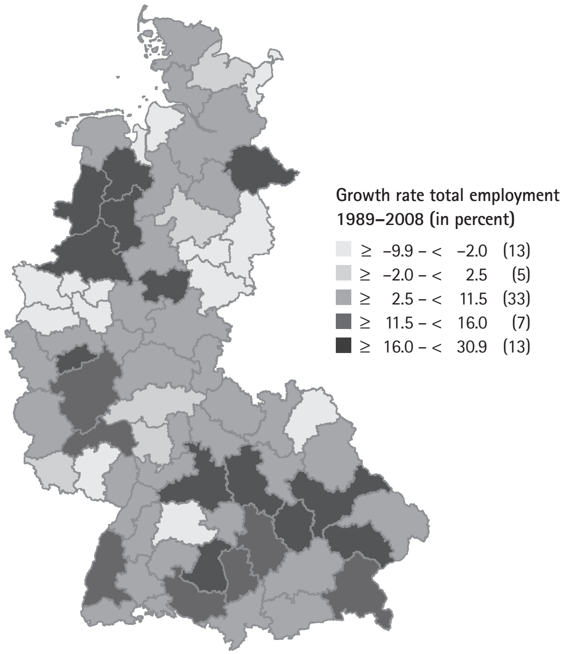
The existing regional evolutions literature dealing with Germany only considers West Germany. Here, also a PVAR including all German regional planning units is considered. However, these findings have to be interpreted with caution because it is not appropriate to consider the results from the model pooling all German regional planning units as the response of the "average" German region. Pronounced labor market disparities between East and West Germany are still observable. The results from the model pooling all German regional planning units indicates that the adjustment processes after a labor demand shock might also differ between East and West Germany. Unfortunately, they provide no insights why differences between East and West Germany occur, and do not allow to quantify these differences.

Even 20 years after reunification, the labor market conditions in East and West Germany are still heterogeneous. Nevertheless, the two parts appear to be closely connected. This can be seen, for example, in the pattern of the mobility flows in Germany. Thus, the two parts of Germany should not be examined separately when examining adjustment processes after a region-specific shock. The results of this study also support this point of view. The specification of a PVAR that allows to map the differences during the adjustment process in East and West appears to be an important topic for further research about labor market dynamics after a region-specific shock in Germany.

Appendix

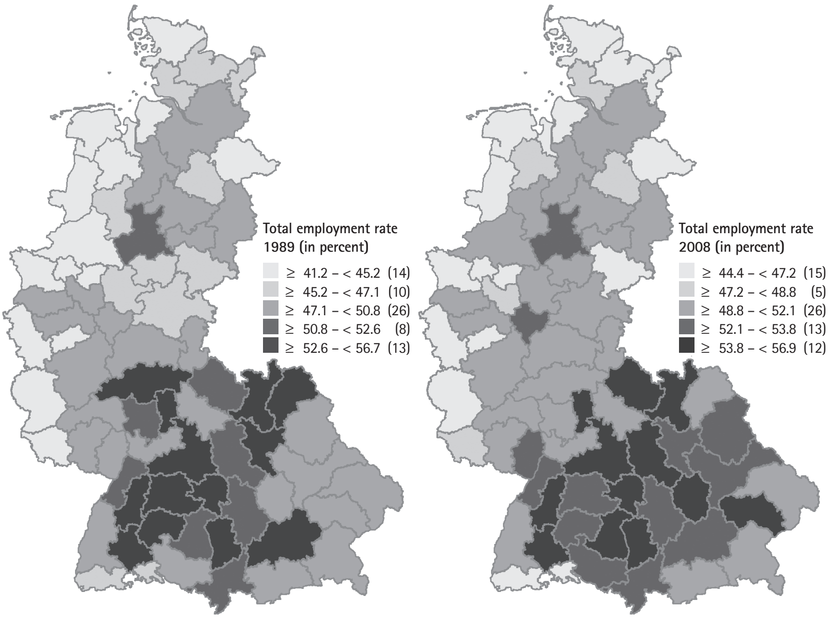
A.1 Appendix: Figures

Figure A.1: Employment growth West German regional planning units, 1989–2008



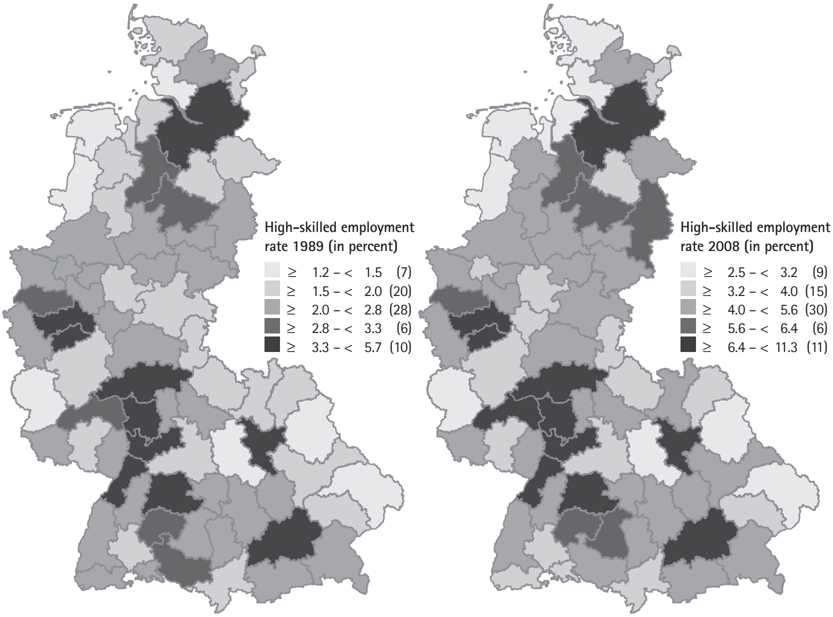
Source: Statistic of the German Federal Employment Agency, own calculations.

Figure A.2: Total employment rates West German regional planning units, 1989 and 2008



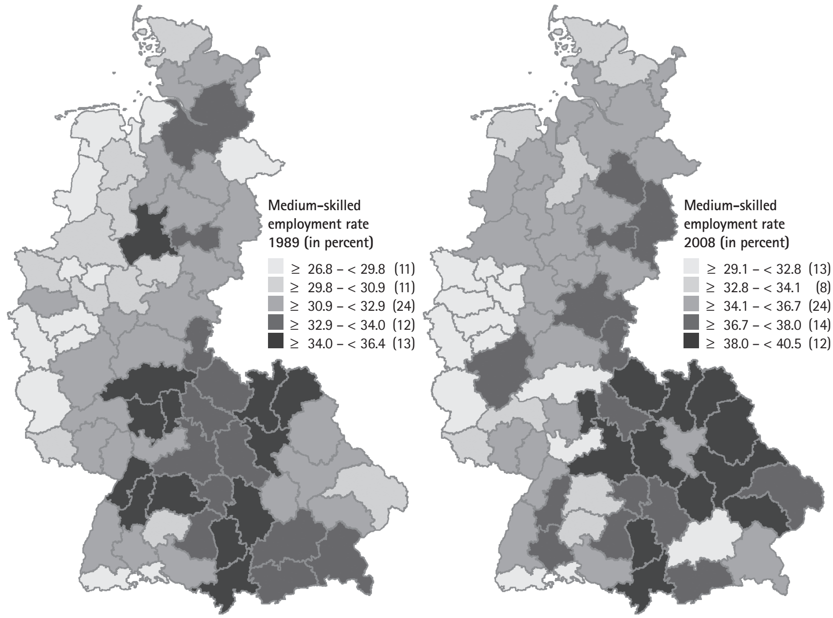
Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

Figure A.3: High-skilled employment rates West German regional planning units, 1989 and 2008



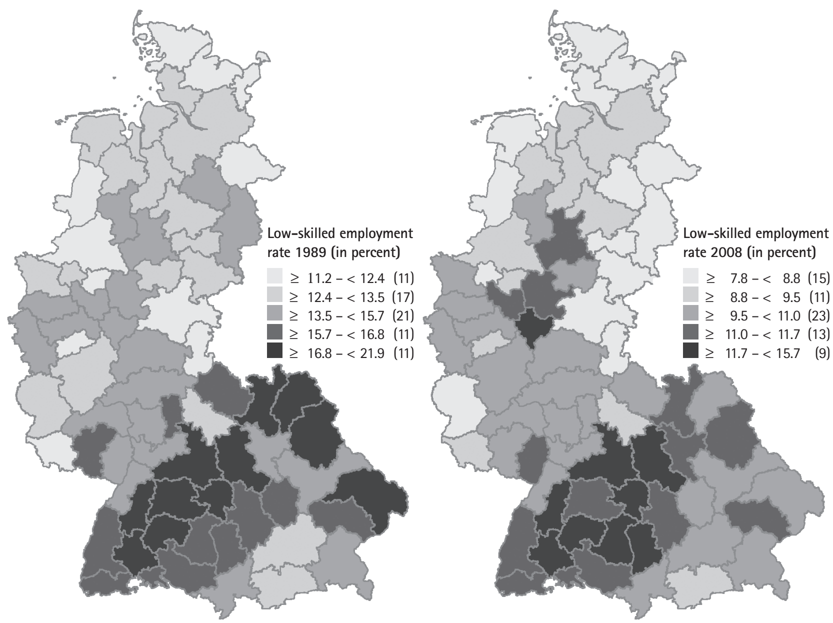
Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

Figure A.4: Medium-skilled employment rates West German regional planning units, 1989 and 2008



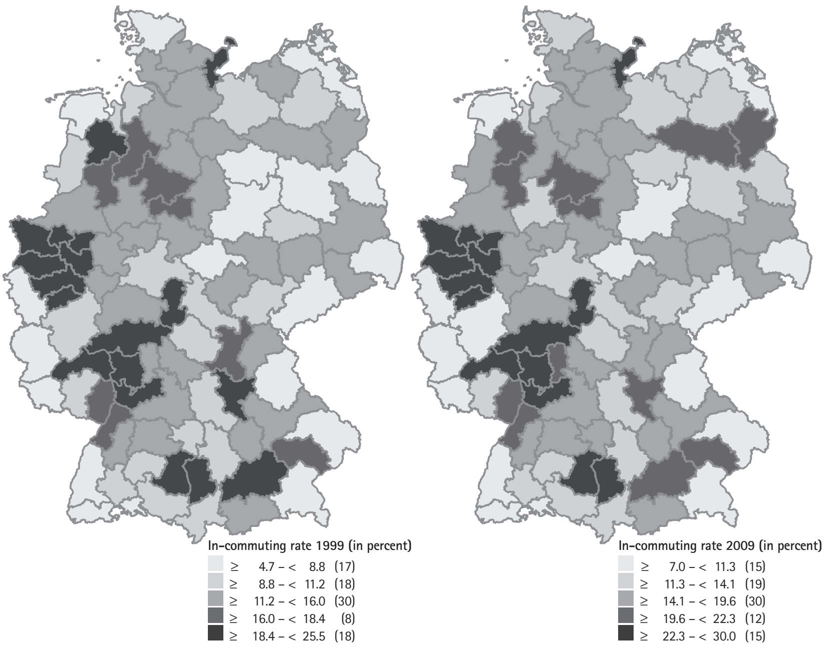
Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

Figure A.5: Low-skilled employment rates West German regional planning units, 1989 and 2008



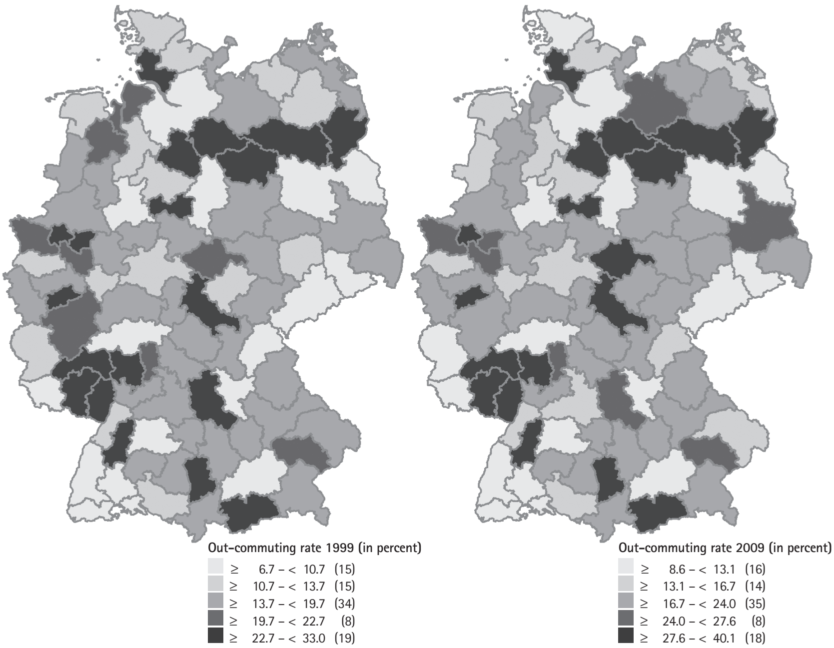
Source: Statistic of the German Federal Employment Agency, Federal Institute for Research on Building, Urban Affairs and Spatial Development, own calculations.

Figure A.6: In-commuting rates German regional planning units, 1999 and 2009



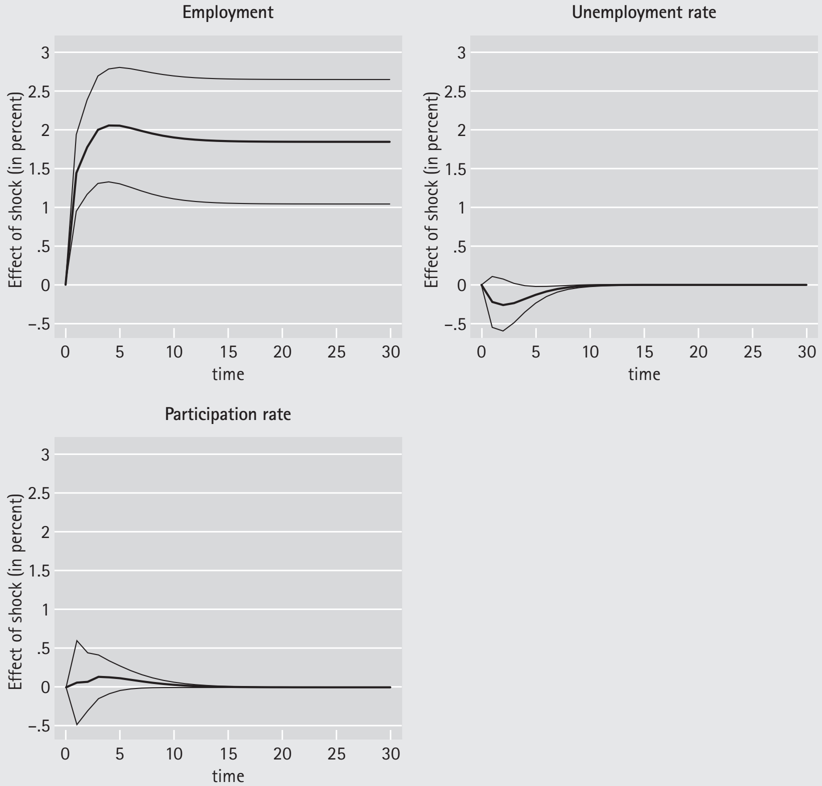
Source: Statistic of the German Federal Employment Agency, own calculations.

Figure A.7: Out-commuting rates German regional planning units, 1999 and 2009



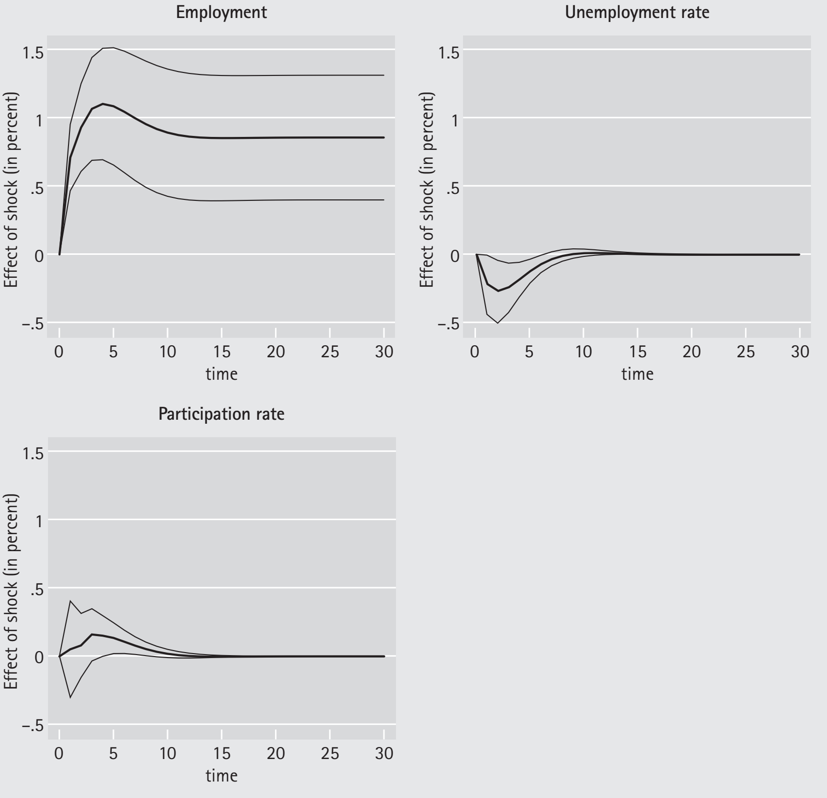
Source: Statistic of the German Federal Employment Agency, own calculations.

Figure A.8: Response of employment, unemployment and participation to a labor demand shock with estimated two-standard error bounds (West German districts, 1989 to 2004)



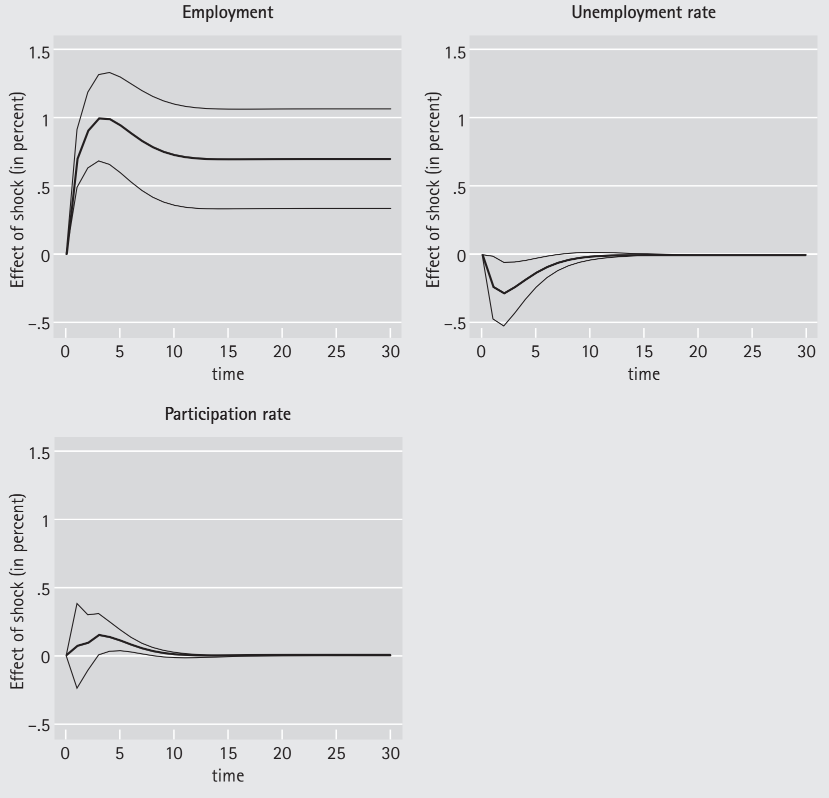
Source: Own calculations.

Figure A.9: Response of employment, unemployment and participation to a labor demand shock with estimated two-standard error bounds (West German regional planning units, 1989 to 2004)



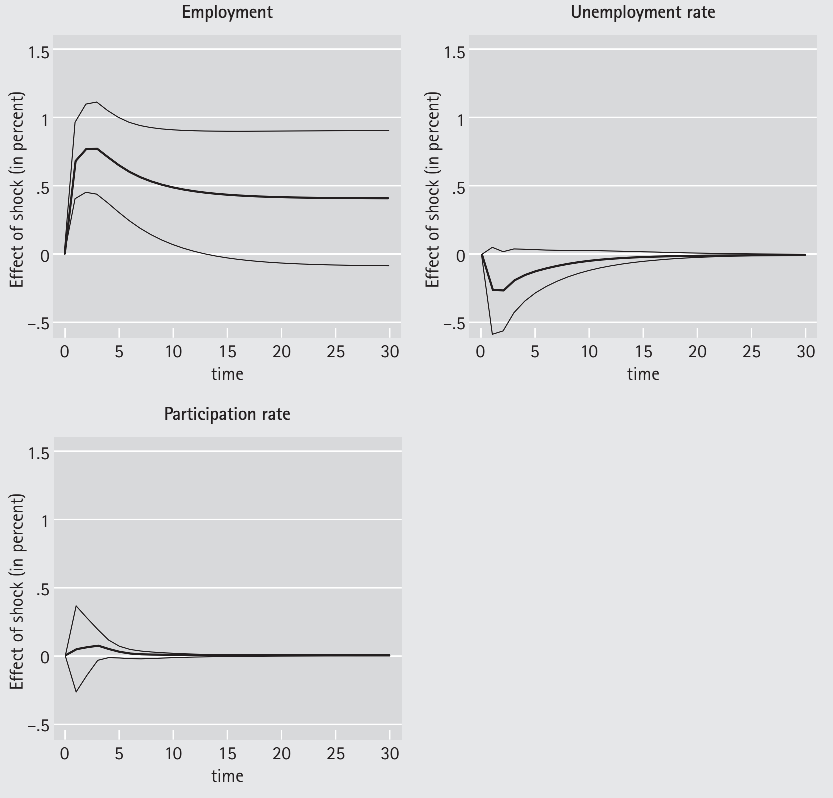
Source: Own calculations.

Figure A.10: Response of employment, unemployment and participation to a labor demand shock with estimated two-standard error bounds (West German regional planning units, 1989 to 2009)



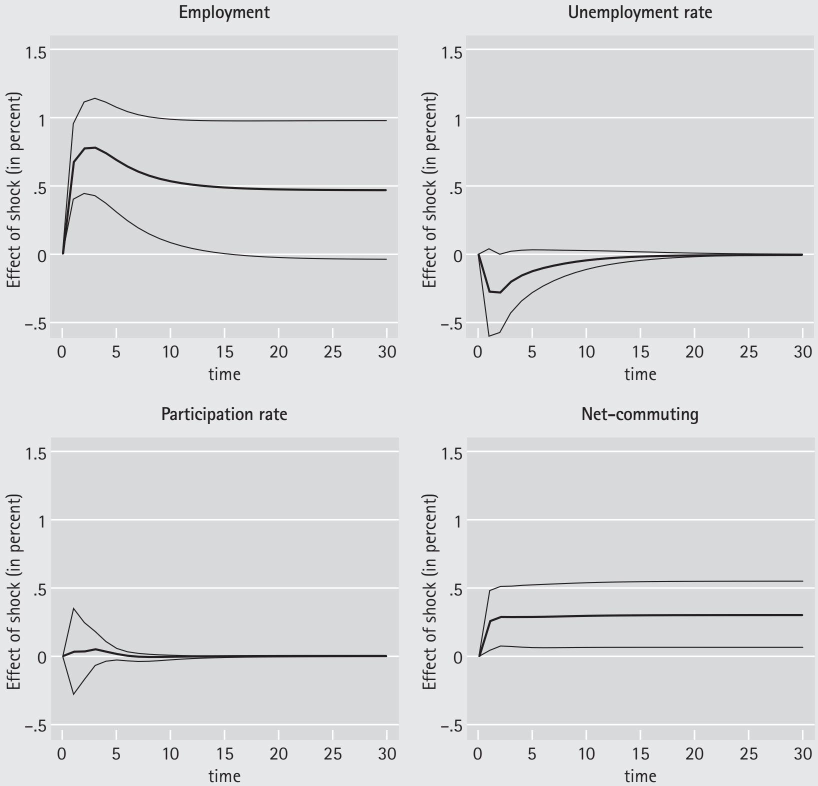
Source: Own calculations.

Figure A.11: Response of employment, unemployment and participation to a labor demand shock with estimated two-standard error bounds (West German regional planning units, 1999 to 2009)



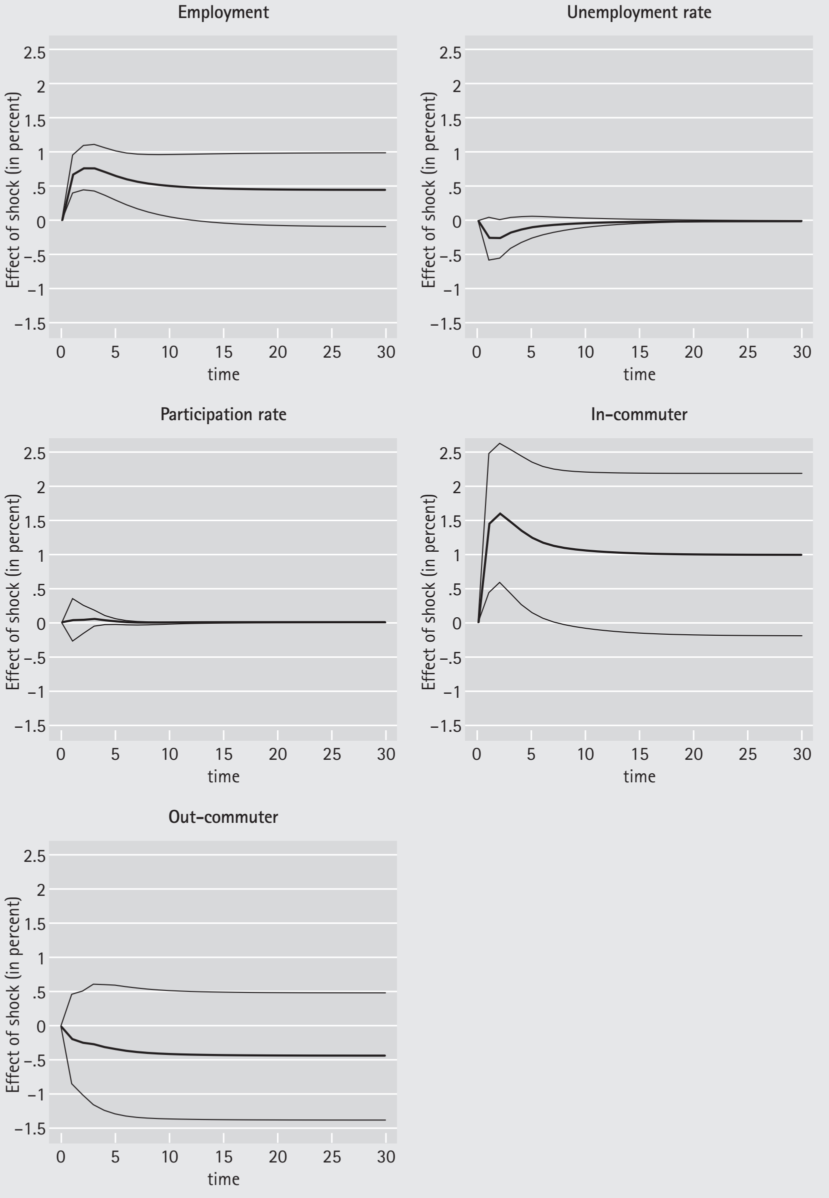
Source: Own calculations.

Figure A.12: Response of employment, unemployment, participation and net-commuting to a labor demand shock with estimated two-standard error bounds (West German regional planning units, 1999 to 2009)



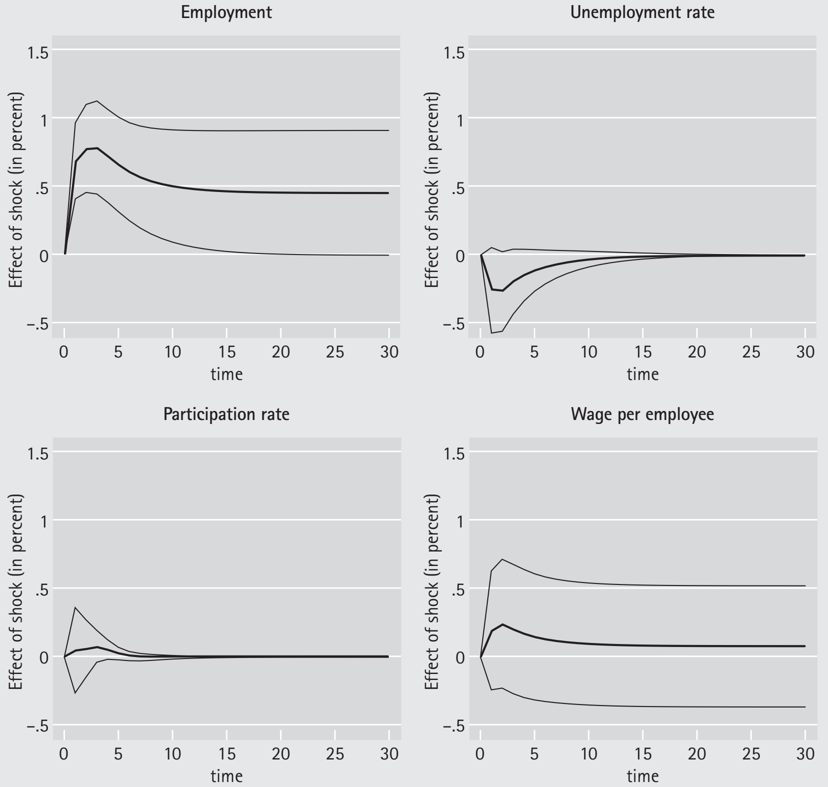
Source: Own calculations.

Figure A.13: Response of employment, unemployment, participation and gross-commuting to a labor demand shock with estimated two-standard error bounds (West German regional planning units, 1999 to 2009)



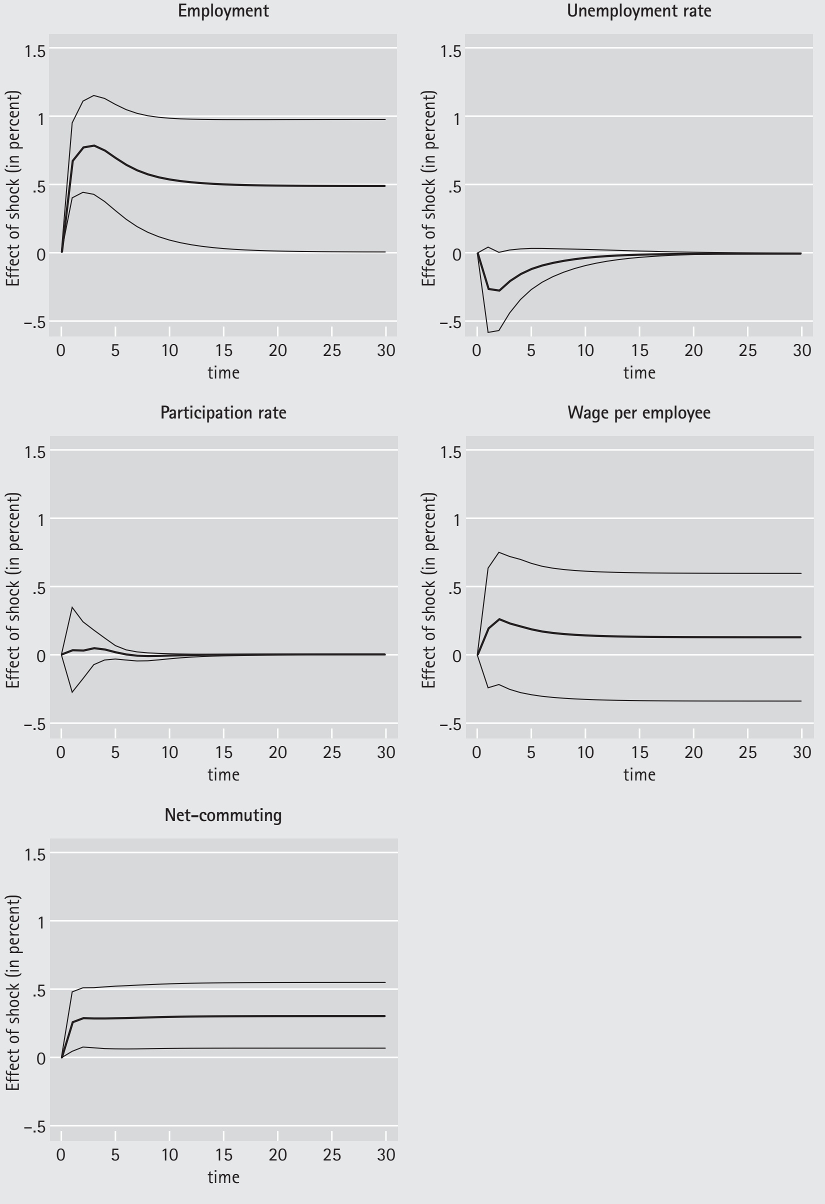
Source: Own calculations.

Figure A.14: Response of employment, wages, unemployment and participation to a labor demand shock with estimated two-standard error bounds (West German regional planning units, 1999 to 2009)



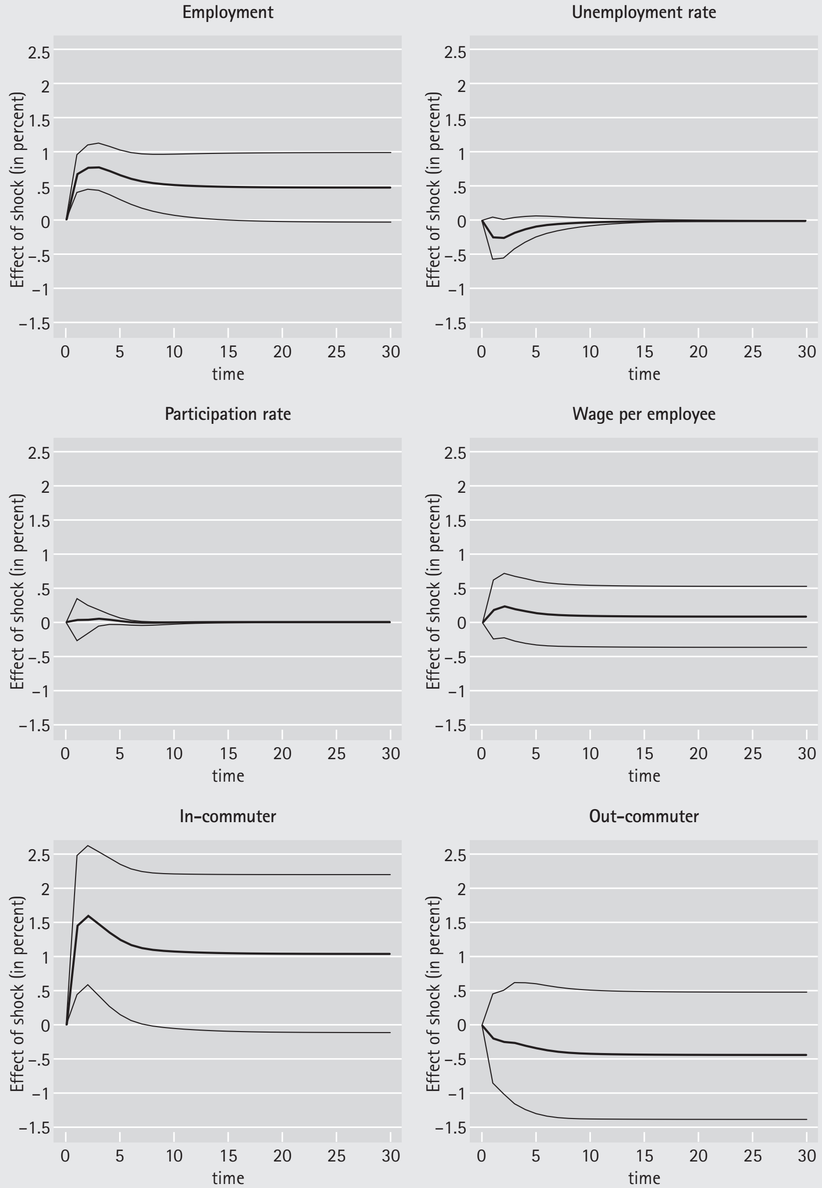
Source: Own calculations.

Figure A.15: Response of employment, wages, unemployment, participation and net-commuting to a labor demand shock with estimated two-standard error bounds (West German regional planning units, 1999 to 2009)



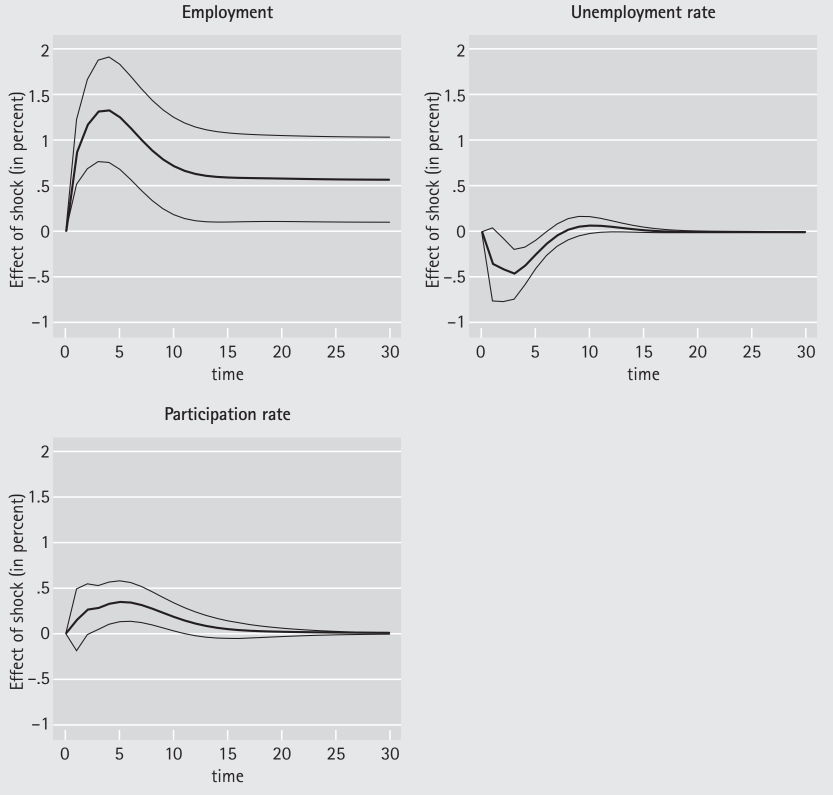
Source: Own calculations.

Figure A.16: Response of employment, wages, unemployment, participation and gross-commuting to a labor demand shock with estimated two-standard error bounds (West German regional planning units, 1999 to 2009)



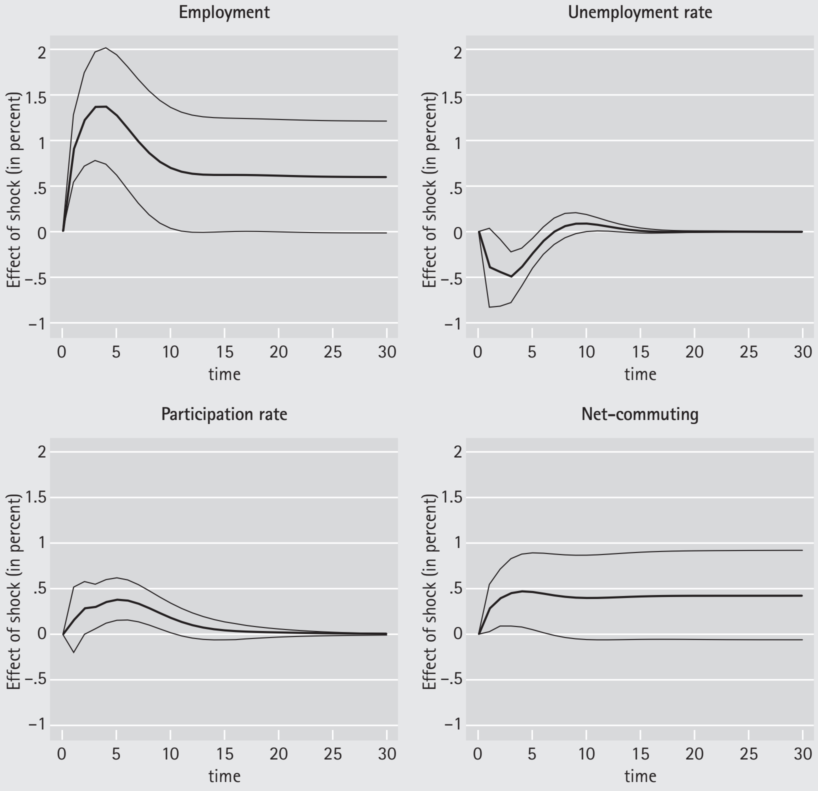
Source: Own calculations.

Figure A.17: Response of employment, unemployment and participation to a labor demand shock with estimated two-standard error bounds (German regional planning units, 1999 to 2009)



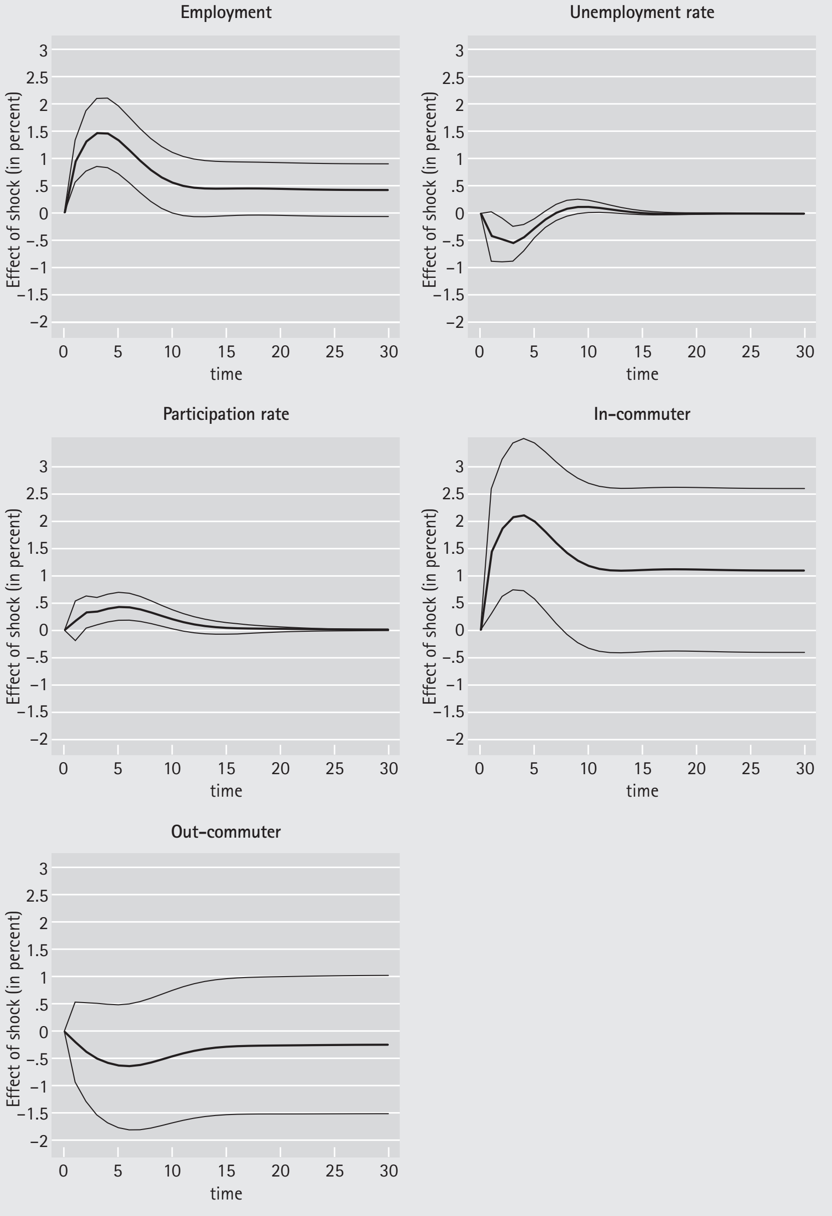
Source: Own calculations.

Figure A.18: Response of employment, unemployment, participation and net-commuting to a labor demand shock with estimated two-standard error bounds (German regional planning units, 1999 to 2009)



Source: Own calculations.

Figure A.19: Response of employment, unemployment, participation and gross-commuting to a labor demand shock with estimated two-standard error bounds (German regional planning units, 1999 to 2009)



Source: Own calculations.

A.2 Appendix: Regression results

Table A.1: Regression results PVAR West German districts, 1989–2004

	Dependent variable		
Regressors	$\tilde{\gamma}^n_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$
$\tilde{\gamma}^n_{t-1}$	0.228*	0.025*	0.010
$\tilde{\gamma}^n_{t-2}$	0.123*	0.015	0.044*
$\tilde{le}_{t-1}$	-0.005	1.013*	0.069*
$\tilde{le}_{t-2}$	-0.090*	-0.269*	0.002
$\tilde{pr}_{t-1}$	-0.021	0.015	0.692*
$\tilde{pr}_{t-2}$	-0.127*	0.009	0.035*
N obs.	5216	5216	5216

Source: Own calculations, * denote significant on the five percent level.

Table A.2: Regression results PVAR West German regional planning units, 1989–2004

	Dependent variable		
Regressors	$\tilde{\gamma}^n_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$
$\tilde{\gamma}^n_{t-1}$	0.313*	0.062*	0.051
$\tilde{\gamma}^n_{t-2}$	0.134*	0.022	0.113*
$\tilde{le}_{t-1}$	-0.016	1.032*	0.038
$\tilde{le}_{t-2}$	-0.068	-0.299*	-0.007
$\tilde{pr}_{t-1}$	0.000	0.020	0.653*
$\tilde{pr}_{t-2}$	-0.170*	-0.020	0.080*
N obs.	1136	1136	1136

Source: Own calculations, * denote significant on the five percent level.

Table A.3: Regression results PVAR West German regional planning units, 1989–2009

	Dependent variable		
Regressors	$\tilde{\gamma}^n_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$
$\tilde{\gamma}^n_{t-1}$	0.322*	0.069*	0.055
$\tilde{\gamma}^n_{t-2}$	0.101*	-0.015	0.098*
$\tilde{le}_{t-1}$	-0.064	0.993*	0.047
$\tilde{le}_{t-2}$	-0.065	-0.206*	-0.002
$\tilde{pr}_{t-1}$	-0.057*	0.027	0.647*
$\tilde{pr}_{t-2}$	-0.114*	-0.025	0.034
N obs.	1491	1491	1491

Source: Own calculations, * denote significant on the five percent level.

Table A.4: Regression results PVAR West German regional planning units, 1999–2009

	Dependent variable		
Regressors	$\tilde{\gamma}^n_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$
$\tilde{\gamma}^n_{t-1}$	0.117*	0.021	-0.017
$\tilde{\gamma}^n_{t-2}$	0.076	-0.053	0.039
$\tilde{le}_{t-1}$	0.045	0.935*	0.165*
$\tilde{le}_{t-2}$	-0.242*	-0.127*	-0.102
$\tilde{pr}_{t-1}$	-0.061	0.128*	0.702*
$\tilde{pr}_{t-2}$	-0.100	0.000	-0.189*
N obs.	781	781	781

Source: Own calculations, * denote significant on the five percent level.

Table A.5: Regression results PVAR West German regional planning units including net-commuting activity, 1999–2009

	Dependent variable			
Regressors	$\tilde{\gamma}^{n}_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$	$\tilde{\gamma}^{ca}_{i,t}$
$\tilde{\gamma}^{n}_{t-1}$	0.385*	0.026	-0.019	0.026
$\tilde{\gamma}^{n}_{t-2}$	0.016	-0.084	0.126*	-0.017
$\tilde{le}_{t-1}$	-0.099	0.916*	0.177*	0.077
$\tilde{le}_{t-2}$	-0.064	-0.112	-0.131*	-0.042
$\tilde{pr}_{t-1}$	-0.129*	0.123*	0.697*	-0.014
$\tilde{pr}_{t-2}$	-0.035	0.003	-0.200*	-0.027
$\tilde{\gamma}^{ca}_{t-1}$	-0.485*	0.029	-0.086	-0.029
$\tilde{\gamma}^{ca}_{t-2}$	0.090	0.079	-0.212*	0.002
N obs.	781	781	781	781

Source: Own calculations, * denote significant on the five percent level.

Table A.6: Regression results PVAR West German regional planning units including gross-commuting activity, 1999–2009

	Dependent variable				
Regressors	$\tilde{\gamma}^{n}_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$	$\tilde{\gamma}^{oc}_{i,t}$	$\tilde{\gamma}^{ic}_{i,t}$
$\tilde{\gamma}^{n}_{t-1}$	0.250*	-0.008	-0.026	-0.171	0.271
$\tilde{\gamma}^{n}_{t-2}$	0.067	-0.164*	0.131*	0.087	-0.092
$\tilde{le}_{t-1}$	-0.027	0.919*	0.162*	-0.047	0.267
$\tilde{le}_{t-2}$	-0.188*	-0.117	-0.125*	-0.046	-0.549*
$\tilde{pr}_{t-1}$	-0.099	0.122*	0.695*	-0.121	-0.157
$\tilde{pr}_{t-2}$	-0.074	0.013	-0.196*	-0.016	-0.274
$\tilde{\gamma}^{oc}_{t-1}$	0.044	0.022	0.014	0.152*	0.058
$\tilde{\gamma}^{oc}_{t-2}$	0.009	0.027	0.031	0.168*	0.052
$\tilde{\gamma}^{ic}_{t-1}$	-0.040	0.020	-0.002	0.073*	-0.063
$\tilde{\gamma}^{ic}_{t-2}$	0.004	0.051*	-0.033	-0.003	0.021
N obs.	781	781	781	781	781

Source: Own calculations, * denote significant on the five percent level.

Table A.7: Regression results PVAR West German regional planning units including wages, 1999–2009

Regressors	Dependent variable $\tilde{\gamma}^{n}_{i,t}$	$\tilde{\gamma}^{wa}_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$
$\tilde{\gamma}^{n}_{t-1}$	0.112*	0.043	0.001	-0.001
$\tilde{\gamma}^{n}_{t-2}$	0.070	–0.029	–0.055	0.021
$\tilde{\gamma}^{wa}_{t-1}$	0.046	0.064	0.134*	-0.056
$\tilde{\gamma}^{wa}_{t-2}$	0.042	–0.007	0.031	0.090*
$\tilde{le}_{t-1}$	0.030	0.028	0.907*	0.152*
$\tilde{le}_{t-2}$	–0.234*	–0.118	–0.115*	–0.099
$\tilde{pr}_{t-1}$	–0.062	–0.012	0.121*	0.704*
$\tilde{pr}_{t-2}$	–0.100	–0.009	0.000	–0.187*
N obs.	781	781	781	781

Source: Own calculations, * denote significant on the five percent level.

Table A.8: Regression results PVAR West German regional planning units including wages and net-commuting activity, 1999–2009

Regressors	Dependent variable $\tilde{\gamma}^{n}_{i,t}$	$\tilde{\gamma}^{wa}_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$	$\tilde{\gamma}^{ca}_{i,t}$
$\tilde{\gamma}^{n}_{t-1}$	0.379*	0.183*	0.003	0.007	0.020
$\tilde{\gamma}^{n}_{t-2}$	0.004	-0.101	-0.090	0.105*	-0.015
$\tilde{\gamma}^{wa}_{t-1}$	0.053	0.075	0.138*	-0.064*	0.013
$\tilde{\gamma}^{wa}_{t-2}$	0.061	-0.003	0.032	0.091*	-0.030
$\tilde{le}_{t-1}$	-0.115	-0.048	0.891*	0.158*	0.081
$\tilde{le}_{t-2}$	-0.058	-0.020	-0.100	-0.122*	-0.042
$\tilde{pr}_{t-1}$	-0.128*	-0.043	0.118*	0.696*	-0.015
$\tilde{pr}_{t-2}$	-0.037	0.028	0.001	-0.195*	-0.027
$\tilde{\gamma}^{ca}_{t-1}$	-0.489*	-0.203*	0.030	-0.101	-0.025
$\tilde{\gamma}^{ca}_{t-2}$	0.097	0.143	0.090	-0.207*	0.004
N obs.	781	781	781	781	781

Source: Own calculations, * denote significant on the five percent level.

Table A.9: Regression results PVAR West German regional planning units including wages and gross-commuting activity, 1999–2009

Regressors	Dependent variable $\tilde{\gamma}^{n}_{i,t}$	$\tilde{\gamma}^{wa}_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$	$\tilde{\gamma}^{oc}_{i,t}$	$\tilde{\gamma}^{ic}_{i,t}$
$\tilde{\gamma}^{n}_{t-1}$	0.248*	0.086	-0.038	0.007	-0.172	0.261
$\tilde{\gamma}^{n}_{t-2}$	0.057	-0.127	-0.168*	0.104	0.063	-0.084
$\tilde{\gamma}^{wa}_{t-1}$	0.040	0.061	0.132*	-0.064*	0.068	0.002
$\tilde{\gamma}^{wa}_{t-2}$	0.046	-0.004	0.035	0.086*	0.099	-0.039
$\tilde{le}_{t-1}$	-0.042	-0.030	0.901*	0.142*	-0.077	0.269
$\tilde{le}_{t-2}$	-0.181*	-0.058	-0.112	-0.114	-0.030	-0.546*
$\tilde{pr}_{t-1}$	-0.099	-0.036	0.121*	0.693*	-0.121	-0.159
$\tilde{pr}_{t-2}$	-0.074	0.029	0.009	-0.191*	-0.014	-0.273
$\tilde{\gamma}^{oc}_{t-1}$	0.043	0.069*	0.017	0.018	0.152*	0.056
$\tilde{\gamma}^{oc}_{t-2}$	0.006	0.004	0.021	0.031	0.164*	0.052
$\tilde{\gamma}^{ic}_{t-1}$	-0.040	0.007	0.023	-0.006	0.072*	-0.061
$\tilde{\gamma}^{ic}_{t-2}$	0.005	0.038	0.050*	-0.029	-0.001	0.020
N obs.	781	781	781	781	781	781

Source: Own calculations, * denote significant on the five percent level.

Table A.10: Regression results PVAR German regional planning units, 1999–2009

Regressors	Dependent variable $\tilde{\gamma}^{n}_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$
$\tilde{\gamma}^{n}_{t-1}$	0.260*	0.133*	0.050
$\tilde{\gamma}^{n}_{t-2}$	0.120*	0.166*	-0.061*
$\tilde{le}_{t-1}$	0.207*	0.825*	0.247*
$\tilde{le}_{t-2}$	-0.308*	-0.203*	-0.040
$\tilde{pr}_{t-1}$	0.003	0.051	0.902*
$\tilde{pr}_{t-2}$	-0.109	-0.030	-0.043
N obs.	1001	1001	1001

Source: Own calculations, * denote significant on the five percent level.

Table A.11: Regression results PVAR German regional planning units including net-commuting activity, 1999–2009

	Dependent variable			
Regressors	$\tilde{\gamma}^{n}_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$	$\tilde{\gamma}^{ca}_{i,t}$
$\tilde{\gamma}^{n}_{t-1}$	0.374*	0.156*	0.008	0.119*
$\tilde{\gamma}^{n}_{t-2}$	0.039	0.217*	-0.071*	-0.024
$\tilde{le}_{t-1}$	0.033	0.766*	0.288*	-0.026
$\tilde{le}_{t-2}$	-0.156*	-0.185*	-0.053	-0.009
$\tilde{pr}_{t-1}$	-0.225*	-0.022	0.920*	-0.075
$\tilde{pr}_{t-2}$	0.086	0.040	-0.067	0.080
$\tilde{\gamma}^{ca}_{t-1}$	-0.001	0.034	0.077	0.102
$\tilde{\gamma}^{ca}_{t-2}$	0.307*	-0.072	-0.021	0.189*
N obs.	1001	1001	1001	1001

Source: Own calculations, * denote significant on the five percent level.

Table A.12: Regression results PVAR German regional planning units including gross-commuting activity, 1999–2009

	Dependent variable				
Regressors	$\tilde{\gamma}^{n}_{i,t}$	$\tilde{le}_{i,t}$	$\tilde{pr}_{i,t}$	$\tilde{\gamma}^{oc}_{i,t}$	$\tilde{\gamma}^{ic}_{i,t}$
$\tilde{\gamma}^{n}_{t-1}$	0.346*	0.154*	0.052	-0.220*	0.219
$\tilde{\gamma}^{n}_{t-2}$	0.051	0.254*	-0.180*	0.004	-0.109
$\tilde{le}_{t-1}$	0.223*	0.845*	0.277*	-0.064	0.442*
$\tilde{le}_{t-2}$	-0.335*	-0.278*	-0.029	-0.011	-0.522*
$\tilde{pr}_{t-1}$	-0.006	0.098	0.888*	-0.156	0.094
$\tilde{pr}_{t-2}$	-0.123	-0.053	-0.042	0.188	-0.189
$\tilde{\gamma}^{oc}_{t-1}$	-0.046	-0.091*	0.012	0.218*	0.099
$\tilde{\gamma}^{oc}_{t-2}$	0.058	0.077*	-0.017	0.063	0.040
$\tilde{\gamma}^{ic}_{t-1}$	-0.043	-0.035	0.011	0.086*	0.021
$\tilde{\gamma}^{ic}_{t-2}$	0.039	-0.030	0.057*	0.013	0.032
N obs.	1001	1001	1001	1001	1001

Source: Own calculations, * denote significant on the five percent level.

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Abstract

This book deals with the question of whether regional disparities in labor market performance widen, become narrower or remain constant over time. It examines the hypothesis of convergence for the unemployment rates of the German Federal States and employment rates of western German regional planning units. Additionally, skill-specific employment rates are considered in order to investigate the relationship between the change in the skill composition of employment and the development of regional employment disparities. The results for the regional unemployment rates are fairly mixed: they provide no evidence that regional inequality clearly increased or decreased over time. Evidence of convergence is found for regional total and high-skilled employment rates. In contrast, the hypothesis of convergence has to be rejected for regional low-skilled and medium-skilled employment rates. In other words, while the changes in the skill composition of employment do not seem to affect the geographical distribution of employment prospects for total employment, they do seem to have an effect on skill-specific employment prospects across regions. Finally, the relationship between adjustment processes after a region-specific labor demand shock and the existence of regional labor market disparities for western German regional planning units is examined. Unemployment, labor force participation, and labor mobility are considered to be the main adjustment channels in the wake of a region-specific labor demand shock. A panel vector autoregressive (PVAR) model is applied to analyze the role of these labor market measures during the adjustment process in the aftermath of a shock. The results show that slow adjustment processes after a region-specific labor demand shock are a possible explanation for persistent disparities in regional unemployment. As in previous studies, labor mobility is identified as being the main adjustment mechanism in the aftermath of a regional labor demand shock. However, a more detailed look at labor mobility shows that here commuting is more important than migration.

Kurzfassung

Dieses Buch beschäftigt sich mit der Frage, ob sich regionale Arbeitsmarktdisparitäten über die Zeit vertiefen, verringern oder ob sie stabil bleiben. Die Konvergenzhypothese wird für die Arbeitslosenquoten deutscher Bundesländer und die Beschäftigungsquoten westdeutscher Raumordnungsregionen überprüft. Um die Auswirkungen des qualifikatorischen Wandels der Beschäftigten auf die Entwicklung regionaler Beschäftigungsdisparitäten aufzuzeigen, werden zusätzlich qualifikationsspezifische Beschäftigungsquoten betrachtet. Es findet sich kein eindeutiger Hinweis darauf, dass die Unterschiede zwischen den Bundesländern hinsichtlich deren Arbeitslosenquoten im Zeitverlauf deutlich zu- oder abgenommen haben. Hinweise auf Konvergenz finden sich im Fall der regionalen Beschäftigungsquoten aller Beschäftigten und der Beschäftigungsquoten für Hochqualifizierte, jedoch nicht für die regionalen Beschäftigungsquoten der Beschäftigten ohne Berufsausbildung sowie der Beschäftigten mit abgeschlossener Berufsausbildung. Der Wandel der Qualifikationsstruktur der Beschäftigten beeinflusst nicht die regionale Verteilung der Beschäftigungschancen insgesamt. Er scheint jedoch Auswirkungen auf die regionale Verteilung der qualifikationsspezifischen Beschäftigungschancen zu haben. Weiterhin wird der Zusammenhang zwischen Anpassungsprozessen nach einem regionalen Arbeitsnachfrageschock und der Existenz regionaler Arbeitsmarktdisparitäten untersucht. Arbeitslosigkeit, Arbeitsmarktpartizipation und Arbeitskräftemobilität gelten als die wichtigsten Anpassungskanäle nach einem solchen Schock. Um die Bedeutung dieser Arbeitsmarktgrößen für den Anpassungsprozess nach einem Schock aufzuzeigen, wird ein Panel-Vektorautoregressives Modell (PVAR) verwendet. Die Ergebnisse zeigen, dass langsame Anpassungsprozesse nach einem regionsspezifischen Arbeitsnachfrageschock eine mögliche Erklärung für dauerhafte regionale Arbeitslosigkeitsdisparitäten sind. Wie in vorangegangenen Arbeiten wird auch hier Arbeitskräftemobilität als wichtigster Anpassungsmechanismus nach einem solchen Schock identifiziert. Eine detaillierte Betrachtung der Arbeitskräftemobilität zeigt, dass dabei das Pendeln eine wichtigere Rolle spielt als Wanderungen.

Numerous countries, Germany among them, are characterized by pronounced regional labor market disparities. Various regional economic studies provide very different approaches to explaining the existence of such variations. However only a few papers give information about the dynamics of regional labor market disparities: Do these increase with time, do they decrease, or do they remain stable? Moreover, the previous studies do not pay attention to the role played in this process by employee groups with differing levels of qualification. Daniel Werner's study closes these gaps. Werner also examines in detail adjustment processes in the wake of regional labor market shocks. His conclusion: The mobility of workers – and here especially commuting – is the most important adjustment mechanism.

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